baseline

December 10, 2025

1 Turbofan Engine RUL Prediction - Baseline Model

Dataset: NASA C-MAPSS (FD001)
Model: Linear Regression Baseline
Goal: Predict Remaining Useful Life (RUL) of turbofan engines

---

1.1 1. Import Libraries

[1]:
```python
%pip install h5py numpy pandas matplotlib seaborn scikit-learn

import h5py
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
import os
import warnings
warnings.filterwarnings('ignore')

plt.style.use('default')
sns.set_style("whitegrid")
plt.rcParams['figure.figsize'] = (12, 6)

print("  All libraries imported successfully!")
```

```
Requirement already satisfied: h5py in
/Users/alyx/miniconda3/envs/cs178/lib/python3.10/site-packages (3.15.1)
Requirement already satisfied: numpy in
/Users/alyx/miniconda3/envs/cs178/lib/python3.10/site-packages (2.2.6)
Requirement already satisfied: pandas in
/Users/alyx/miniconda3/envs/cs178/lib/python3.10/site-packages (2.3.2)
Requirement already satisfied: matplotlib in
/Users/alyx/miniconda3/envs/cs178/lib/python3.10/site-packages (3.10.6)
```

```
Requirement already satisfied: seaborn in
/Users/alyx/miniconda3/envs/cs178/lib/python3.10/site-packages (0.13.2)
Requirement already satisfied: scikit-learn in
/Users/alyx/miniconda3/envs/cs178/lib/python3.10/site-packages (1.7.2)
Requirement already satisfied: python-dateutil>=2.8.2 in
/Users/alyx/miniconda3/envs/cs178/lib/python3.10/site-packages (from pandas)
(2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in
/Users/alyx/miniconda3/envs/cs178/lib/python3.10/site-packages (from pandas)
(2025.2)
Requirement already satisfied: tzdata>=2022.7 in
/Users/alyx/miniconda3/envs/cs178/lib/python3.10/site-packages (from pandas)
(2025.2)
Requirement already satisfied: contourpy>=1.0.1 in
/Users/alyx/miniconda3/envs/cs178/lib/python3.10/site-packages (from matplotlib)
(1.3.2)
Requirement already satisfied: cycler>=0.10 in
/Users/alyx/miniconda3/envs/cs178/lib/python3.10/site-packages (from matplotlib)
(0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/Users/alyx/miniconda3/envs/cs178/lib/python3.10/site-packages (from matplotlib)
(4.60.0)
Requirement already satisfied: kiwisolver>=1.3.1 in
/Users/alyx/miniconda3/envs/cs178/lib/python3.10/site-packages (from matplotlib)
(1.4.9)
Requirement already satisfied: packaging>=20.0 in
/Users/alyx/miniconda3/envs/cs178/lib/python3.10/site-packages (from matplotlib)
(25.0)
Requirement already satisfied: pillow>=8 in
/Users/alyx/miniconda3/envs/cs178/lib/python3.10/site-packages (from matplotlib)
(11.3.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/Users/alyx/miniconda3/envs/cs178/lib/python3.10/site-packages (from matplotlib)
(3.2.5)
Requirement already satisfied: scipy>=1.8.0 in
/Users/alyx/miniconda3/envs/cs178/lib/python3.10/site-packages (from scikit-
learn) (1.15.2)
Requirement already satisfied: joblib>=1.2.0 in
/Users/alyx/miniconda3/envs/cs178/lib/python3.10/site-packages (from scikit-
learn) (1.5.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in
/Users/alyx/miniconda3/envs/cs178/lib/python3.10/site-packages (from scikit-
learn) (3.6.0)
Requirement already satisfied: six>=1.5 in
/Users/alyx/miniconda3/envs/cs178/lib/python3.10/site-packages (from python-
dateutil>=2.8.2->pandas) (1.17.0)
Note: you may need to restart the kernel to use updated packages.
 All libraries imported successfully!
```

1.2 2. Configuration

[2]:
```
DATA_PATH = 'CMaps/'
FILENAME = 'N-CMAPSS_DS02-006.h5'
WINDOW_SIZE = 30
TEST_SIZE = 0.10
VAL_SIZE = 0.10
RANDOM_STATE = 42

print("Configuration:")
print(f"  Dataset: {FILENAME}")
print(f"  Window Size: {WINDOW_SIZE}")
print(f"  Train/Val/Test Split: {(1-TEST_SIZE-VAL_SIZE)*100:.0f}/{VAL_SIZE*100:.
  ↪0f}/{TEST_SIZE*100:.0f}")
print(f"  Random State: {RANDOM_STATE}")
```

```
Configuration:
  Dataset: N-CMAPSS_DS02-006.h5
  Window Size: 30
  Train/Val/Test Split: 80/10/10
  Random State: 42
```

1.3 3. Data Loader

[3]:
```
h5path = os.path.join(DATA_PATH, FILENAME)
hdf = h5py.File(h5path, 'r')

print("N-CMAPSS HDF5 File Structure:")
print("="*60)
for key in hdf.keys():
    print(f"{key:15s}   shape: {hdf[key].shape}   dtype: {hdf[key].dtype}")
print("="*60)
```

```
N-CMAPSS HDF5 File Structure:
============================================================
A_dev            shape: (5263447, 4)   dtype: float64
A_test           shape: (1253743, 4)   dtype: float64
A_var            shape: (4,)   dtype: |S5
T_dev            shape: (5263447, 10)   dtype: float64
T_test           shape: (1253743, 10)   dtype: float64
T_var            shape: (10,)   dtype: |S12
W_dev            shape: (5263447, 4)   dtype: float64
W_test           shape: (1253743, 4)   dtype: float64
W_var            shape: (4,)   dtype: |S4
X_s_dev          shape: (5263447, 14)   dtype: float64
X_s_test         shape: (1253743, 14)   dtype: float64
X_s_var          shape: (14,)   dtype: |S4
X_v_dev          shape: (5263447, 14)   dtype: float64
X_v_test         shape: (1253743, 14)   dtype: float64
```

```
X_v_var             shape: (14,)   dtype: |S5
Y_dev               shape: (5263447, 1)   dtype: int64
Y_test              shape: (1253743, 1)   dtype: int64
============================================================
```

1.4 4. Helper Function and Load Variable Names

[4]:
```python
def decode(byte_array):
    return [x.decode('utf-8') for x in byte_array]

A_var = decode(hdf["A_var"])
W_var = decode(hdf["W_var"])
Xs_var = decode(hdf["X_s_var"])
Xv_var = decode(hdf["X_v_var"])

if "T_var" in hdf:
    T_var = decode(hdf["T_var"])
    print("T columns:", T_var)

print("A columns (Auxiliary):", A_var)
print("W columns (Operating):", W_var)
print("Xs columns (Physical Sensors):", Xs_var)
print("Xv columns (Virtual Sensors - EXCLUDED):", Xv_var[:5], "...")
```

```
T columns: ['fan_eff_mod', 'fan_flow_mod', 'LPC_eff_mod', 'LPC_flow_mod',
'HPC_eff_mod', 'HPC_flow_mod', 'HPT_eff_mod', 'HPT_flow_mod', 'LPT_eff_mod',
'LPT_flow_mod']
A columns (Auxiliary): ['unit', 'cycle', 'Fc', 'hs']
W columns (Operating): ['alt', 'Mach', 'TRA', 'T2']
Xs columns (Physical Sensors): ['T24', 'T30', 'T48', 'T50', 'P15', 'P2', 'P21',
'P24', 'Ps30', 'P40', 'P50', 'Nf', 'Nc', 'Wf']
Xv columns (Virtual Sensors - EXCLUDED): ['T40', 'P30', 'P45', 'W21', 'W22'] …
```

1.5 5. Load Training Data

[5]:
```python
A_dev = hdf["A_dev"][:]
W_dev = hdf["W_dev"][:]
Xs_dev = hdf["X_s_dev"][:]
Y_dev = hdf["Y_dev"][:]

print("Data loaded:")
print(f"  A_dev (Auxiliary): {A_dev.shape}")
print(f"  W_dev (Operating): {W_dev.shape}")
print(f"  Xs_dev (Sensors): {Xs_dev.shape}")
print(f"  Y_dev (RUL): {Y_dev.shape}")

df_A = pd.DataFrame(A_dev, columns=A_var)
df_W = pd.DataFrame(W_dev, columns=W_var)
```

```python
df_Xs = pd.DataFrame(Xs_dev, columns=Xs_var)

df_dev = pd.concat([df_A, df_W, df_Xs], axis=1)
df_dev['RUL'] = Y_dev[:, 0]

print(f"\n Combined dataframe shape: {df_dev.shape}")
print(f" Columns: {list(df_dev.columns)}")
df_dev.head()
```

```
Data loaded:
  A_dev (Auxiliary): (5263447, 4)
  W_dev (Operating): (5263447, 4)
  Xs_dev (Sensors): (5263447, 14)
  Y_dev (RUL): (5263447, 1)

 Combined dataframe shape: (5263447, 23)
 Columns: ['unit', 'cycle', 'Fc', 'hs', 'alt', 'Mach', 'TRA', 'T2', 'T24',
'T30', 'T48', 'T50', 'P15', 'P2', 'P21', 'P24', 'Ps30', 'P40', 'P50', 'Nf',
'Nc', 'Wf', 'RUL']
```

[5]:

```
   unit  cycle   Fc   hs      alt      Mach        TRA          T2  \
0   2.0    1.0  3.0  1.0  10005.0  0.448497  76.903748  502.420918
1   2.0    1.0  3.0  1.0  10013.0  0.447741  76.903748  502.326114
2   2.0    1.0  3.0  1.0  10017.0  0.448938  77.079529  502.416067
3   2.0    1.0  3.0  1.0  10024.0  0.449883  77.079529  502.469893
4   2.0    1.0  3.0  1.0  10031.0  0.449379  77.079529  502.401271

          T24          T30  …         P2        P21        P24        Ps30  \
0  600.148034  1438.498187  …  11.577097  16.046971  20.126624  331.293679
1  600.055894  1438.350208  …  11.568235  16.036017  20.113218  331.109867
2  600.210756  1439.109101  …  11.574866  16.048474  20.130956  331.753181
3  600.369717  1439.240230  …  11.578198  16.057218  20.146716  331.819136
4  600.298227  1439.064004  …  11.571593  16.048236  20.135888  331.626003

          P40        P50           Nf           Nc        Wf  RUL
0  336.631827  12.629361  2160.926416  8591.373490  3.855337   74
1  336.446748  12.623033  2160.909333  8590.972866  3.852319   74
2  337.082502  12.637951  2161.819062  8593.031745  3.866201   74
3  337.162828  12.631509  2162.768666  8593.781545  3.863328   74
4  336.966936  12.624872  2162.619544  8593.220200  3.860818   74

[5 rows x 23 columns]
```

1.6 6. Basic Dataset Statistics

[6]:
```python
print("Dataset Statistics:")
print("="*60)
print(f"Number of samples: {len(df_dev):,}")
print(f"Number of engines: {df_dev['unit'].nunique()}")
print(f"Number of cycles: {df_dev['cycle'].nunique()}")
print(f"\nRUL range: [{df_dev['RUL'].min():.0f}, {df_dev['RUL'].max():.0f}]␣
↪cycles")
print(f"RUL mean: {df_dev['RUL'].mean():.1f} cycles")

print("\nCycles per engine:")
print(df_dev.groupby('unit')['cycle'].max())

print("\nSamples per engine:")
print(df_dev.groupby('unit').size())
print("="*60)
```

```
Dataset Statistics:
============================================================
Number of samples: 5,263,447
Number of engines: 6
Number of cycles: 89

RUL range: [0, 88] cycles
RUL mean: 37.3 cycles

Cycles per engine:
unit
2.0     75.0
5.0     89.0
10.0    82.0
16.0    63.0
18.0    71.0
20.0    66.0
Name: cycle, dtype: float64

Samples per engine:
unit
2.0      853142
5.0     1033420
10.0     952711
16.0     765295
18.0     890719
20.0     768160
dtype: int64
============================================================
```

1.7 7. Define Feature Columns

[7]:
```
scenario_cols = ['alt', 'Mach', 'TRA', 'T2']

sensor_cols = [
    'Wf',   # Fuel flow
    'Nf',   # Physical fan speed
    'Nc',   # Physical core speed
    'T24',  # Total temp at LPC outlet
    'T30',  # Total temp at HPC outlet
    'T48',  # Total temp at HPT outlet
    'T50',  # Total temp at LPT outlet
    'P15',  # Total pressure in bypass-duct
    'P2',   # Total pressure at fan inlet
    'P21',  # Total pressure at fan outlet
    'Ps30', # Static pressure at HPC outlet
    'P40',  # Total pressure at burner outlet
    'P50'   # Total pressure at LPT outlet
]

candidate_cols = scenario_cols + sensor_cols

candidate_cols = [col for col in candidate_cols if col in df_dev.columns]

print("Feature columns (17 physical variables per document):")
print(f"  Scenario descriptors: {scenario_cols}")
print(f"  Physical sensors: {sensor_cols}")
print(f"  Total features: {len(candidate_cols)}")
print(f"\n All columns verified in dataset")
```

```
Feature columns (17 physical variables per document):
  Scenario descriptors: ['alt', 'Mach', 'TRA', 'T2']
  Physical sensors: ['Wf', 'Nf', 'Nc', 'T24', 'T30', 'T48', 'T50', 'P15', 'P2',
'P21', 'Ps30', 'P40', 'P50']
  Total features: 17

 All columns verified in dataset
```

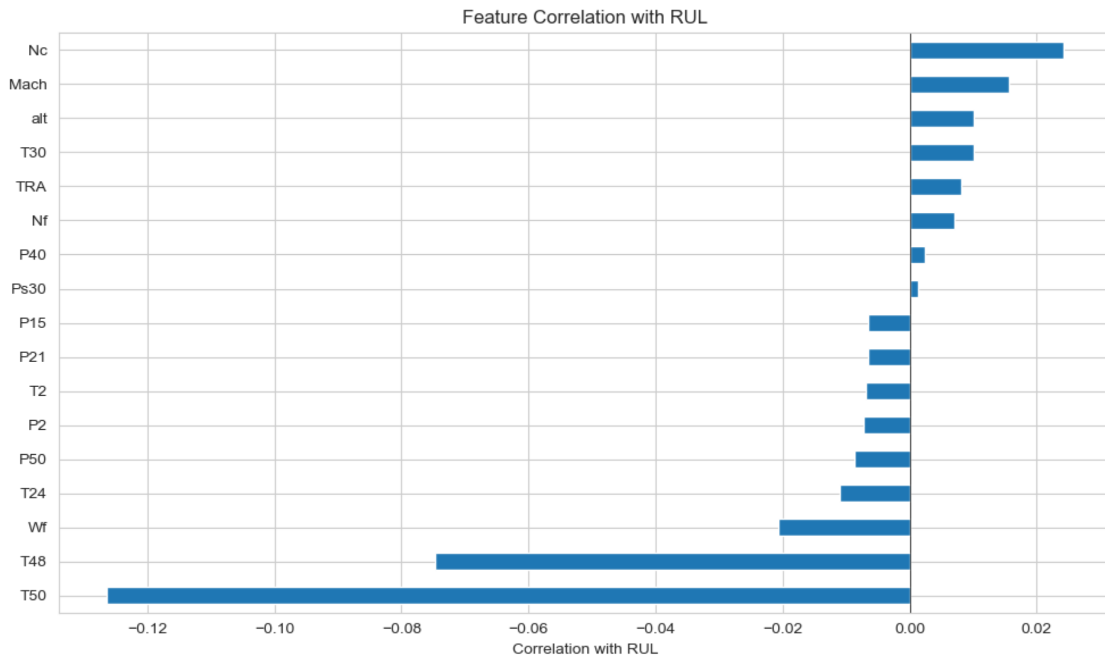
1.8 8. Feature Selection

[8]:
```
print("Feature Selection: Correlation with RUL")
print("="*60)

corr_w_rul = df_dev[candidate_cols + ["RUL"]].corr()["RUL"].drop("RUL")
corr_w_rul = corr_w_rul.reindex(corr_w_rul.abs().sort_values(ascending=False).
 ↪index)

print("\nCorrelation with RUL:")
```

```python
print(corr_w_rul)

k = 10
selected_features = corr_w_rul.abs().head(k).index.tolist()

print(f"\n{'='*60}")
print(f"Selected Features (top {k} by correlation):")
print(f"{'='*60}")
for i, feat in enumerate(selected_features, 1):
    corr_val = corr_w_rul[feat]
    print(f"{i:2d}. {feat:8s}   Correlation: {corr_val:7.4f}")

print(f"\nTotal selected features: {len(selected_features)}")

plt.figure(figsize=(10, 6))
corr_w_rul.sort_values(ascending=True).plot(kind='barh')
plt.xlabel('Correlation with RUL')
plt.title('Feature Correlation with RUL')
plt.axvline(x=0, color='black', linestyle='-', linewidth=0.5)
plt.tight_layout()
plt.show()
```

```
Feature Selection: Correlation with RUL
============================================================

Correlation with RUL:
T50     -0.126475
T48     -0.074675
Nc       0.024205
Wf      -0.020594
Mach     0.015666
T24     -0.011008
alt      0.010162
T30      0.010153
P50     -0.008643
TRA      0.008057
P2      -0.007272
Nf       0.007115
T2      -0.006856
P21     -0.006542
P15     -0.006542
P40      0.002407
Ps30     0.001256
Name: RUL, dtype: float64

============================================================
Selected Features (top 10 by correlation):
============================================================
```

```
 1. T50        Correlation: -0.1265
 2. T48        Correlation: -0.0747
 3. Nc         Correlation:  0.0242
 4. Wf         Correlation: -0.0206
 5. Mach       Correlation:  0.0157
 6. T24        Correlation: -0.0110
 7. alt        Correlation:  0.0102
 8. T30        Correlation:  0.0102
 9. P50        Correlation: -0.0086
10. TRA        Correlation:  0.0081

Total selected features: 10
```



1.9 9. Create Rolling Window Features

[9]:
```python
def create_window_features(df, feature_cols, window_size=30):
    print(f"Creating rolling window features (window={window_size})...")

    feature_list = []

    for unit_id in df['unit'].unique():
        unit_data = df[df['unit'] == unit_id].sort_values('cycle').copy()

        for col in feature_cols:
            if col in unit_data.columns:
```

```
            # Rolling statistics
            unit_data[f'{col}_mean'] = unit_data[col].rolling(
                window=window_size, min_periods=1
            ).mean()

            unit_data[f'{col}_std'] = unit_data[col].rolling(
                window=window_size, min_periods=1
            ).std().fillna(0)

            unit_data[f'{col}_min'] = unit_data[col].rolling(
                window=window_size, min_periods=1
            ).min()

            unit_data[f'{col}_max'] = unit_data[col].rolling(
                window=window_size, min_periods=1
            ).max()

            # Calculate slope (linear trend)
            def calc_slope(series):
                if len(series) < 2:
                    return 0
                x = np.arange(len(series))
                y = series.values
                slope = np.polyfit(x, y, 1)[0]
                return slope

            unit_data[f'{col}_slope'] = unit_data[col].rolling(
                window=window_size, min_periods=2
            ).apply(calc_slope, raw=False).fillna(0)

        feature_list.append(unit_data)

    result_df = pd.concat(feature_list, ignore_index=True)
    print(f"  Window features created. New shape: {result_df.shape}")

    return result_df

df_features = create_window_features(df_dev, selected_features, WINDOW_SIZE)

window_feature_cols = [col for col in df_features.columns
                       if any(stat in col for stat in ['_mean', '_std', '_min',␣
 ↪'_max', '_slope'])]

print(f"\nTotal window features created: {len(window_feature_cols)}")
print(f"Features per sensor: 5 (mean, std, min, max, slope)")
print(f"Expected: {len(selected_features)} × 5 = {len(selected_features)*5}")
```

```
Creating rolling window features (window=30)…
```

```
 Window features created. New shape: (5263447, 73)

Total window features created: 50
Features per sensor: 5 (mean, std, min, max, slope)
Expected: 10 × 5 = 50
```

1.10 10. Prepare Features and Split Data

[10]:
```
X = df_features[window_feature_cols].values
y = df_features['RUL'].values

print(f"Feature matrix: {X.shape}")
print(f"Target vector: {y.shape}")

X_temp, X_test, y_temp, y_test = train_test_split(
    X, y, test_size=TEST_SIZE, random_state=RANDOM_STATE
)

val_size_adjusted = VAL_SIZE / (1 - TEST_SIZE)
X_train, X_val, y_train, y_val = train_test_split(
    X_temp, y_temp, test_size=val_size_adjusted, random_state=RANDOM_STATE
)

print(f"\nData split:")
print(f"  Training:   {X_train.shape[0]:6,} samples ({X_train.shape[0]/
 ↪len(X)*100:5.1f}%)")
print(f"  Validation: {X_val.shape[0]:6,} samples ({X_val.shape[0]/len(X)*100:5.
 ↪1f}%)")
print(f"  Test:       {X_test.shape[0]:6,} samples ({X_test.shape[0]/len(X)*100:
 ↪5.1f}%)")
```

```
Feature matrix: (5263447, 50)
Target vector: (5263447,)

Data split:
  Training:   4,210,757 samples ( 80.0%)
  Validation: 526,345 samples ( 10.0%)
  Test:       526,345 samples ( 10.0%)
```

1.11 11. Train Baseline Model

[11]:
```
print("Training Linear Regression Baseline Model...")
print("="*60)

model = LinearRegression()
scaler = StandardScaler()

X_train_scaled = scaler.fit_transform(X_train)
```

```python
X_val_scaled = scaler.transform(X_val)
X_test_scaled = scaler.transform(X_test)

model.fit(X_train_scaled, y_train)

print("  Model training complete!")

y_train_pred = model.predict(X_train_scaled)
y_val_pred = model.predict(X_val_scaled)
y_test_pred = model.predict(X_test_scaled)

print("  Predictions complete!")
```

```
Training Linear Regression Baseline Model…
============================================================
 Model training complete!
 Predictions complete!
```

1.12 12. Evaluation Metrics

[12]:

```python
from sklearn.metrics import mean_squared_error, mean_absolute_error

def calculate_rmse(y_true, y_pred):
    return np.sqrt(mean_squared_error(y_true, y_pred))

def calculate_nasa_score(y_true, y_pred):
    """
    NASA Scoring Function (asymmetric)
    From document equation (2):
    - Penalizes late predictions less (a = -1/13)
    - Penalizes early predictions more (a = 1/10)
    """
    errors = y_true - y_pred
    score = 0

    for error in errors:
        if error < 0:
            score += np.exp(-error / 13) - 1
        else:
            score += np.exp(error / 10) - 1

    return score

def evaluate_all(y_true, y_pred, dataset_name=""):
    mse = mean_squared_error(y_true, y_pred)
    rmse = calculate_rmse(y_true, y_pred)
    mae = mean_absolute_error(y_true, y_pred)
    nasa_score = calculate_nasa_score(y_true, y_pred)
```

```python
    print(f"\n{'='*60}")
    print(f"{dataset_name} Evaluation Metrics")
    print(f"{'='*60}")
    print(f"MSE:          {mse:10.2f}")
    print(f"RMSE:         {rmse:10.2f}")
    print(f"MAE:          {mae:10.2f}")
    print(f"NASA Score:   {nasa_score:10.2f}")
    print(f"{'='*60}")

    return {'MSE': mse, 'RMSE': rmse, 'MAE': mae, 'NASA_Score': nasa_score}

train_metrics = evaluate_all(y_train, y_train_pred, "Training Set")
val_metrics = evaluate_all(y_val, y_val_pred, "Validation Set")
test_metrics = evaluate_all(y_test, y_test_pred, "Test Set")
```

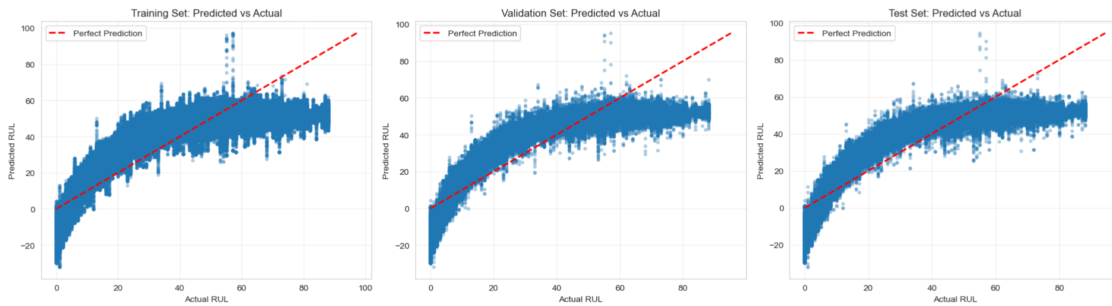
```
============================================================
Training Set Evaluation Metrics
============================================================
MSE:              139.73
RMSE:              11.82
MAE:                9.86
NASA Score:   9201929.28
============================================================

============================================================
Validation Set Evaluation Metrics
============================================================
MSE:              139.51
RMSE:              11.81
MAE:                9.85
NASA Score:   1146810.21
============================================================

============================================================
Test Set Evaluation Metrics
============================================================
MSE:              139.68
RMSE:              11.82
MAE:                9.86
NASA Score:   1149589.51
============================================================
```

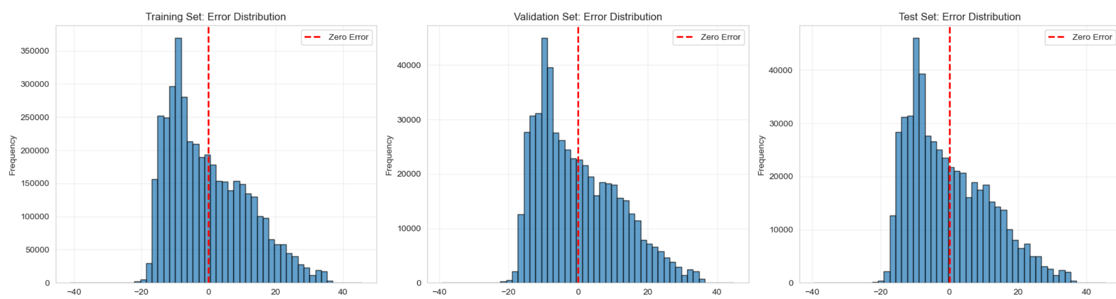
1.13 13. Visualizations

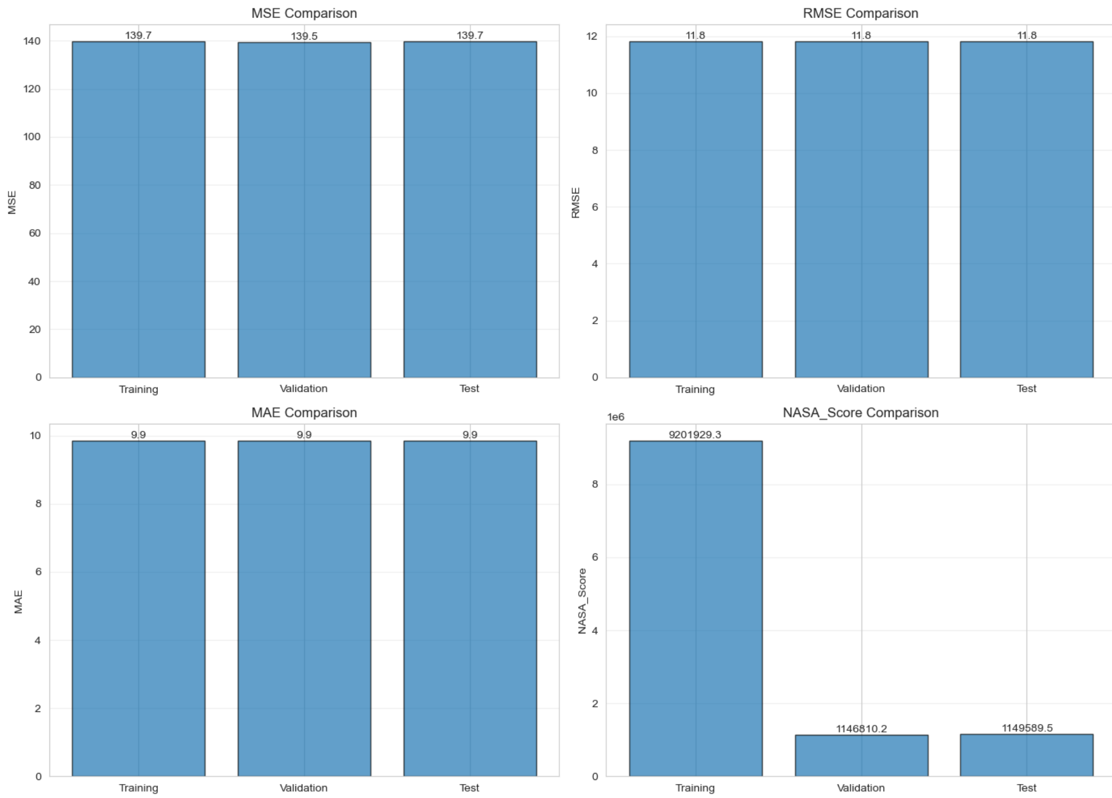
[13]:

```
fig, axes = plt.subplots(1, 3, figsize=(18, 5))

datasets = [
    (y_train, y_train_pred, "Training"),
    (y_val, y_val_pred, "Validation"),
    (y_test, y_test_pred, "Test")
]

for ax, (y_true, y_pred, name) in zip(axes, datasets):
    ax.scatter(y_true, y_pred, alpha=0.3, s=10)
    max_val = max(y_true.max(), y_pred.max())
    ax.plot([0, max_val], [0, max_val], 'r--', lw=2, label='Perfect Prediction')
    ax.set_xlabel('Actual RUL')
    ax.set_ylabel('Predicted RUL')
    ax.set_title(f'{name} Set: Predicted vs Actual')
    ax.legend()
    ax.grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

fig, axes = plt.subplots(1, 3, figsize=(18, 5))

for ax, (y_true, y_pred, name) in zip(axes, datasets):
    errors = y_true - y_pred
    ax.hist(errors, bins=50, edgecolor='black', alpha=0.7)
    ax.axvline(x=0, color='r', linestyle='--', lw=2, label='Zero Error')
    ax.set_xlabel('Prediction Error (Actual - Predicted)')
    ax.set_ylabel('Frequency')
    ax.set_title(f'{name} Set: Error Distribution')
    ax.legend()
    ax.grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

metrics_df = pd.DataFrame({
    'Training': train_metrics,
    'Validation': val_metrics,
    'Test': test_metrics
})

fig, axes = plt.subplots(2, 2, figsize=(14, 10))
metrics = ['MSE', 'RMSE', 'MAE', 'NASA_Score']

for ax, metric in zip(axes.flat, metrics):
```

```
    values = metrics_df.loc[metric]
    bars = ax.bar(values.index, values.values, alpha=0.7, edgecolor='black')
    ax.set_ylabel(metric)
    ax.set_title(f'{metric} Comparison')
    ax.grid(True, alpha=0.3, axis='y')

    for bar in bars:
        height = bar.get_height()
        ax.text(bar.get_x() + bar.get_width()/2., height,
               f'{height:.1f}', ha='center', va='bottom')

plt.tight_layout()
plt.show()
```







1.14 14. Save Results

[14]:
```
os.makedirs('results', exist_ok=True)

with open('results/baseline_results.txt', 'w') as f:
    f.write("="*60 + "\n")
    f.write("N-CMAPSS Baseline Model Results\n")
    f.write("="*60 + "\n\n")

    f.write(f"Dataset: {FILENAME}\n")
    f.write(f"Window Size: {WINDOW_SIZE}\n")
    f.write(f"Selected Features: {len(selected_features)}\n")
    f.write(f"Window Features: {len(window_feature_cols)}\n\n")

    for name, metrics in [('Training', train_metrics),
                          ('Validation', val_metrics),
                          ('Test', test_metrics)]:
        f.write(f"{name} Set:\n")
        for metric, value in metrics.items():
            f.write(f"  {metric}: {value:.2f}\n")
        f.write("\n")
```

```
print("\n" + "="*60)
print("  Baseline model training complete!")
print(f"  Results saved to 'results/baseline_results.txt'")
print("="*60)
```

```
============================================================
 Baseline model training complete!
 Results saved to 'results/baseline_results.txt'
============================================================
```

1.15 15. Regularization Additions

[15]:
```
from sklearn.linear_model import Ridge
import time

print("="*60)
print("Testing Ridge Regression (L2 Regularization)")
print("="*60)

alphas = [0.001, 0.01, 0.1, 1.0, 10.0, 100.0, 1000.0]

results_dict = {
    'Model': [],
    'Alpha': [],
    'Train_RMSE': [],
    'Val_RMSE': [],
    'Test_RMSE': [],
    'Train_MAE': [],
    'Val_MAE': [],
    'Test_MAE': [],
    'Train_NASA': [],
    'Val_NASA': [],
    'Test_NASA': [],
    'Training_Time': []
}

print("\n0. Baseline (No Regularization)")
print("-"*60)
results_dict['Model'].append('Baseline')
results_dict['Alpha'].append(0)
results_dict['Train_RMSE'].append(train_metrics['RMSE'])
results_dict['Val_RMSE'].append(val_metrics['RMSE'])
results_dict['Test_RMSE'].append(test_metrics['RMSE'])
results_dict['Train_MAE'].append(train_metrics['MAE'])
results_dict['Val_MAE'].append(val_metrics['MAE'])
results_dict['Test_MAE'].append(test_metrics['MAE'])
```

```
results_dict['Train_NASA'].append(train_metrics['NASA_Score'])
results_dict['Val_NASA'].append(val_metrics['NASA_Score'])
results_dict['Test_NASA'].append(test_metrics['NASA_Score'])
results_dict['Training_Time'].append(0)

print(f"  Val RMSE: {val_metrics['RMSE']:.2f}")
print(f"  Val NASA: {val_metrics['NASA_Score']:.2f}")

print("\n1. Testing Ridge Regression (L2 Regularization)...")
print("-"*60)

for alpha in alphas:
    print(f"\nAlpha = {alpha}")

    start_time = time.time()

    ridge_model = Ridge(alpha=alpha, random_state=RANDOM_STATE)
    ridge_model.fit(X_train_scaled, y_train)

    training_time = time.time() - start_time

    y_train_pred_ridge = ridge_model.predict(X_train_scaled)
    y_val_pred_ridge = ridge_model.predict(X_val_scaled)
    y_test_pred_ridge = ridge_model.predict(X_test_scaled)

    train_rmse = calculate_rmse(y_train, y_train_pred_ridge)
    val_rmse = calculate_rmse(y_val, y_val_pred_ridge)
    test_rmse = calculate_rmse(y_test, y_test_pred_ridge)

    train_mae = mean_absolute_error(y_train, y_train_pred_ridge)
    val_mae = mean_absolute_error(y_val, y_val_pred_ridge)
    test_mae = mean_absolute_error(y_test, y_test_pred_ridge)

    train_nasa = calculate_nasa_score(y_train, y_train_pred_ridge)
    val_nasa = calculate_nasa_score(y_val, y_val_pred_ridge)
    test_nasa = calculate_nasa_score(y_test, y_test_pred_ridge)

    results_dict['Model'].append('Ridge')
    results_dict['Alpha'].append(alpha)
    results_dict['Train_RMSE'].append(train_rmse)
    results_dict['Val_RMSE'].append(val_rmse)
    results_dict['Test_RMSE'].append(test_rmse)
    results_dict['Train_MAE'].append(train_mae)
    results_dict['Val_MAE'].append(val_mae)
    results_dict['Test_MAE'].append(test_mae)
    results_dict['Train_NASA'].append(train_nasa)
    results_dict['Val_NASA'].append(val_nasa)
```

```
    results_dict['Test_NASA'].append(test_nasa)
    results_dict['Training_Time'].append(training_time)

    print(f"  Val RMSE: {val_rmse:.2f}, Val NASA: {val_nasa:.2f}, Time:␣
↪{training_time:.2f}s")

print("\n" + "="*60)
print("Ridge regularization experiments complete!")
print("="*60)
```

```
============================================================
Testing Ridge Regression (L2 Regularization)
============================================================

0. Baseline (No Regularization)
------------------------------------------------------------
  Val RMSE: 11.81
  Val NASA: 1146810.21

1. Testing Ridge Regression (L2 Regularization)…
------------------------------------------------------------

Alpha = 0.001
  Val RMSE: 11.81, Val NASA: 1146810.22, Time: 2.06s

Alpha = 0.01
  Val RMSE: 11.81, Val NASA: 1146810.36, Time: 1.65s

Alpha = 0.1
  Val RMSE: 11.81, Val NASA: 1146811.74, Time: 1.78s

Alpha = 1.0
  Val RMSE: 11.81, Val NASA: 1146829.21, Time: 2.04s

Alpha = 10.0
  Val RMSE: 11.81, Val NASA: 1147179.24, Time: 1.89s

Alpha = 100.0
  Val RMSE: 11.83, Val NASA: 1150126.49, Time: 2.01s

Alpha = 1000.0
  Val RMSE: 11.90, Val NASA: 1167486.83, Time: 2.12s

============================================================
Ridge regularization experiments complete!
============================================================
```

1.16 16. Visualization of Regularization

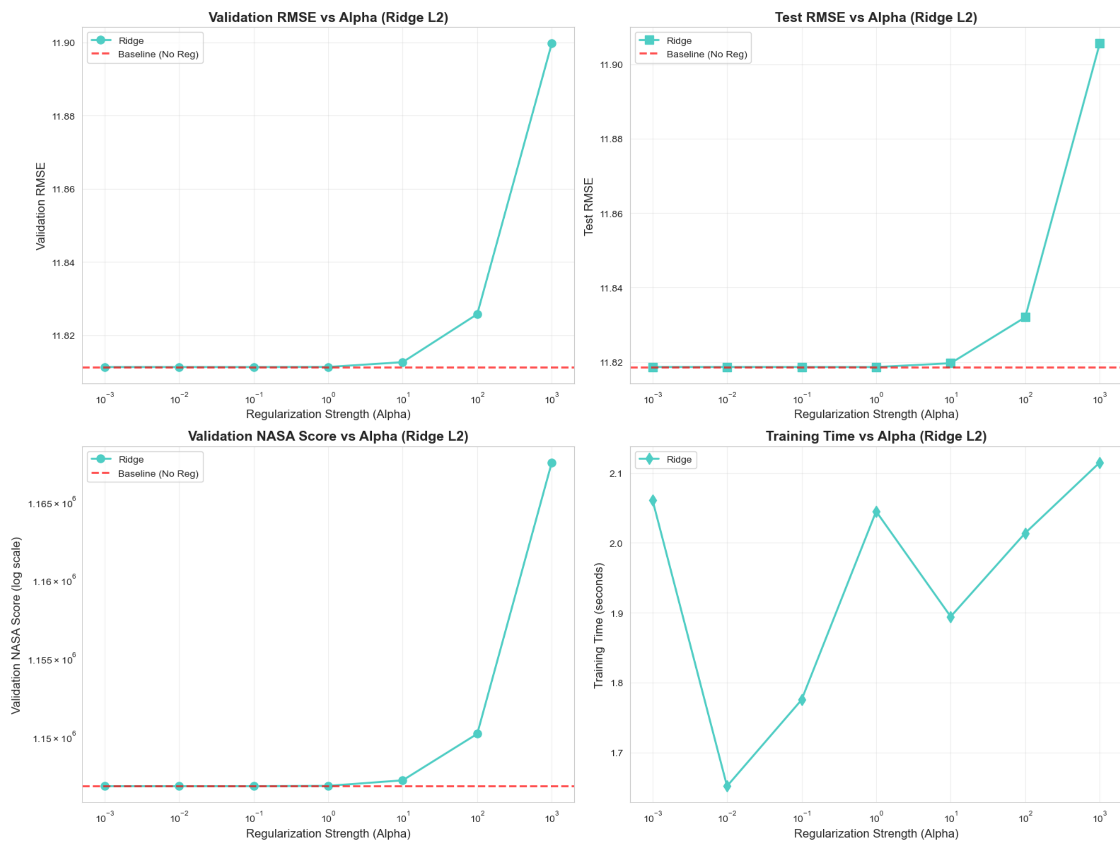
[16]:
```
results_df = pd.DataFrame(results_dict)

print("\nRidge Regularization Results:")
print("="*100)
print(results_df.to_string(index=False))
print("="*100)

print("\n  Best Ridge Models by Validation RMSE:")
print("-"*60)
best_5 = results_df.nsmallest(5, 'Val_RMSE')[['Model', 'Alpha', 'Val_RMSE',␣
↪'Test_RMSE', 'Val_NASA', 'Test_NASA']]
print(best_5.to_string(index=False))

print("\n  Best Ridge Models by Validation NASA Score:")
print("-"*60)
best_5_nasa = results_df.nsmallest(5, 'Val_NASA')[['Model', 'Alpha',␣
↪'Val_RMSE', 'Test_RMSE', 'Val_NASA', 'Test_NASA']]
print(best_5_nasa.to_string(index=False))

fig, axes = plt.subplots(2, 2, figsize=(16, 12))

ax = axes[0, 0]
ridge_data = results_df[results_df['Model'] == 'Ridge']
baseline_rmse = results_df[results_df['Model'] == 'Baseline']['Val_RMSE'].
↪values[0]

ax.semilogx(ridge_data['Alpha'], ridge_data['Val_RMSE'],
            marker='o', label='Ridge', linewidth=2, markersize=8,␣
↪color='#4ECDC4')
ax.axhline(y=baseline_rmse, color='red', linestyle='--',
           linewidth=2, label='Baseline (No Reg)', alpha=0.7)

ax.set_xlabel('Regularization Strength (Alpha)', fontsize=12)
ax.set_ylabel('Validation RMSE', fontsize=12)
ax.set_title('Validation RMSE vs Alpha (Ridge L2)', fontsize=14,␣
↪fontweight='bold')
ax.legend(fontsize=10)
ax.grid(True, alpha=0.3)

ax = axes[0, 1]
baseline_test_rmse = results_df[results_df['Model'] == 'Baseline']['Test_RMSE'].
↪values[0]

ax.semilogx(ridge_data['Alpha'], ridge_data['Test_RMSE'],
```

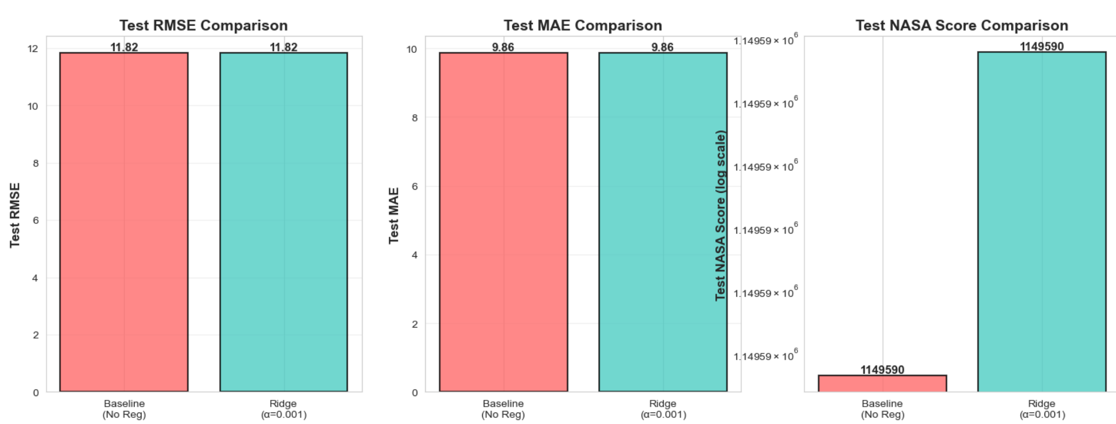
```
             marker='s', label='Ridge', linewidth=2, markersize=8,␣
↪color='#4ECDC4')
ax.axhline(y=baseline_test_rmse, color='red', linestyle='--',
           linewidth=2, label='Baseline (No Reg)', alpha=0.7)

ax.set_xlabel('Regularization Strength (Alpha)', fontsize=12)
ax.set_ylabel('Test RMSE', fontsize=12)
ax.set_title('Test RMSE vs Alpha (Ridge L2)', fontsize=14, fontweight='bold')
ax.legend(fontsize=10)
ax.grid(True, alpha=0.3)

ax = axes[1, 0]
baseline_nasa = results_df[results_df['Model'] == 'Baseline']['Val_NASA'].
↪values[0]

ax.loglog(ridge_data['Alpha'], ridge_data['Val_NASA'],
          marker='o', label='Ridge', linewidth=2, markersize=8, color='#4ECDC4')
ax.axhline(y=baseline_nasa, color='red', linestyle='--',
           linewidth=2, label='Baseline (No Reg)', alpha=0.7)

ax.set_xlabel('Regularization Strength (Alpha)', fontsize=12)
ax.set_ylabel('Validation NASA Score (log scale)', fontsize=12)
ax.set_title('Validation NASA Score vs Alpha (Ridge L2)', fontsize=14,␣
↪fontweight='bold')
ax.legend(fontsize=10)
ax.grid(True, alpha=0.3)

ax = axes[1, 1]
ax.semilogx(ridge_data['Alpha'], ridge_data['Training_Time'],
            marker='d', label='Ridge', linewidth=2, markersize=8,␣
↪color='#4ECDC4')

ax.set_xlabel('Regularization Strength (Alpha)', fontsize=12)
ax.set_ylabel('Training Time (seconds)', fontsize=12)
ax.set_title('Training Time vs Alpha (Ridge L2)', fontsize=14,␣
↪fontweight='bold')
ax.legend(fontsize=10)
ax.grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

fig, axes = plt.subplots(1, 3, figsize=(18, 6))

baseline_row = results_df[results_df['Model'] == 'Baseline'].iloc[0]
best_ridge = results_df[results_df['Model'] == 'Ridge'].nsmallest(1,␣
↪'Val_RMSE').iloc[0]
```

```python
comparison_data = pd.DataFrame({
    'Model': [
        f"Baseline\n(No Reg)",
        f"Ridge\n( ={best_ridge['Alpha']})"
    ],
    'Test_RMSE': [baseline_row['Test_RMSE'], best_ridge['Test_RMSE']],
    'Test_MAE': [baseline_row['Test_MAE'], best_ridge['Test_MAE']],
    'Test_NASA': [baseline_row['Test_NASA'], best_ridge['Test_NASA']]
})

ax = axes[0]
bars = ax.bar(comparison_data['Model'], comparison_data['Test_RMSE'],
              color=['#FF6B6B', '#4ECDC4'], alpha=0.8, edgecolor='black', linewidth=1.5)
ax.set_ylabel('Test RMSE', fontsize=12, fontweight='bold')
ax.set_title('Test RMSE Comparison', fontsize=14, fontweight='bold')
ax.grid(True, alpha=0.3, axis='y')
for bar in bars:
    height = bar.get_height()
    ax.text(bar.get_x() + bar.get_width()/2., height,
            f'{height:.2f}',
            ha='center', va='bottom', fontsize=11, fontweight='bold')

ax = axes[1]
bars = ax.bar(comparison_data['Model'], comparison_data['Test_MAE'],
              color=['#FF6B6B', '#4ECDC4'], alpha=0.8, edgecolor='black', linewidth=1.5)
ax.set_ylabel('Test MAE', fontsize=12, fontweight='bold')
ax.set_title('Test MAE Comparison', fontsize=14, fontweight='bold')
ax.grid(True, alpha=0.3, axis='y')
for bar in bars:
    height = bar.get_height()
    ax.text(bar.get_x() + bar.get_width()/2., height,
            f'{height:.2f}',
            ha='center', va='bottom', fontsize=11, fontweight='bold')

ax = axes[2]
bars = ax.bar(comparison_data['Model'], comparison_data['Test_NASA'],
              color=['#FF6B6B', '#4ECDC4'], alpha=0.8, edgecolor='black', linewidth=1.5)
ax.set_ylabel('Test NASA Score (log scale)', fontsize=12, fontweight='bold')
ax.set_title('Test NASA Score Comparison', fontsize=14, fontweight='bold')
ax.set_yscale('log')
ax.grid(True, alpha=0.3, axis='y')
for bar in bars:
    height = bar.get_height()
```

```
    ax.text(bar.get_x() + bar.get_width()/2., height,
            f'{height:.0f}',
            ha='center', va='bottom', fontsize=11, fontweight='bold')
```

```
Ridge Regularization Results:
================================================================================
====================
   Model    Alpha  Train_RMSE  Val_RMSE  Test_RMSE  Train_MAE  Val_MAE  Test_MAE
Train_NASA     Val_NASA    Test_NASA  Training_Time
Baseline    0.000    11.820745 11.811242  11.818655   9.860341 9.852740  9.858246
9.201929e+06 1.146810e+06 1.149590e+06       0.000000
   Ridge    0.001    11.820745 11.811242  11.818655   9.860341 9.852740  9.858246
9.201929e+06 1.146810e+06 1.149590e+06       2.061390
   Ridge    0.010    11.820745 11.811242  11.818655   9.860341 9.852740  9.858246
9.201929e+06 1.146810e+06 1.149590e+06       1.651548
   Ridge    0.100    11.820745 11.811243  11.818652   9.860340 9.852741  9.858243
9.201932e+06 1.146812e+06 1.149590e+06       1.775162
   Ridge    1.000    11.820768 11.811270  11.818646   9.860344 9.852763  9.858232
9.201987e+06 1.146829e+06 1.149599e+06       2.044943
   Ridge   10.000    11.822032 11.812584  11.819683   9.861253 9.853761  9.859008
9.204182e+06 1.147179e+06 1.149892e+06       1.894332
   Ridge  100.000    11.835145 11.825709  11.832014   9.871118 9.864061  9.868289
9.226700e+06 1.150126e+06 1.152728e+06       2.013930
   Ridge 1000.000    11.910547 11.899754  11.905569   9.920449 9.913131  9.916087
9.375648e+06 1.167487e+06 1.170145e+06       2.115031
================================================================================
====================

 Best Ridge Models by Validation RMSE:
------------------------------------------------------------
   Model  Alpha  Val_RMSE  Test_RMSE     Val_NASA    Test_NASA
Baseline  0.000 11.811242  11.818655 1.146810e+06 1.149590e+06
   Ridge  0.001 11.811242  11.818655 1.146810e+06 1.149590e+06
   Ridge  0.010 11.811242  11.818655 1.146810e+06 1.149590e+06
   Ridge  0.100 11.811243  11.818652 1.146812e+06 1.149590e+06
   Ridge  1.000 11.811270  11.818646 1.146829e+06 1.149599e+06

 Best Ridge Models by Validation NASA Score:
------------------------------------------------------------
   Model  Alpha  Val_RMSE  Test_RMSE     Val_NASA    Test_NASA
Baseline  0.000 11.811242  11.818655 1.146810e+06 1.149590e+06
   Ridge  0.001 11.811242  11.818655 1.146810e+06 1.149590e+06
   Ridge  0.010 11.811242  11.818655 1.146810e+06 1.149590e+06
   Ridge  0.100 11.811243  11.818652 1.146812e+06 1.149590e+06
   Ridge  1.000 11.811270  11.818646 1.146829e+06 1.149599e+06
```





1.17 17. Save Updated Results

[17]:
```
results_df.to_csv('results/ridge_regularization_results.csv', index=False)
print("\n Results saved to 'results/ridge_regularization_results.csv'")

with open('results/ridge_regularization_summary.txt', 'w') as f:
```

```
    f.write("="*80 + "\n")
    f.write("RIDGE (L2) REGULARIZATION EXPERIMENT SUMMARY\n")
    f.write("="*80 + "\n\n")

    f.write(f"Dataset: {FILENAME}\n")
    f.write(f"Test Set Size: {X_test.shape[0]:,} input-output pairs\n")
    f.write(f"Input Features: {X_test.shape[1]} window features\n")
    f.write(f"Models Tested: Baseline, Ridge (L2)\n")
    f.write(f"Alpha values tested: {alphas}\n\n")

    f.write("="*80 + "\n")
    f.write("BEST RIDGE MODELS BY VALIDATION RMSE\n")
    f.write("="*80 + "\n")
    f.write(best_5.to_string(index=False))
    f.write("\n\n")

    f.write("="*80 + "\n")
    f.write("BEST RIDGE MODELS BY VALIDATION NASA SCORE\n")
    f.write("="*80 + "\n")
    f.write(best_5_nasa.to_string(index=False))
    f.write("\n\n")

    f.write("="*80 + "\n")
    f.write("BEST RIDGE MODEL\n")
    f.write("="*80 + "\n")
    best_overall = results_df.nsmallest(1, 'Val_RMSE').iloc[0]
    f.write(f"\nBest Overall Model (by Val RMSE):\n")
    f.write(f"  Alpha: {best_overall['Alpha']}\n")
    f.write(f"  Val RMSE: {best_overall['Val_RMSE']:.2f}\n")
    f.write(f"  Test RMSE: {best_overall['Test_RMSE']:.2f}\n")
    f.write(f"  Val NASA: {best_overall['Val_NASA']:.2f}\n")
    f.write(f"  Test NASA: {best_overall['Test_NASA']:.2f}\n")

    baseline_row = results_df[results_df['Model'] == 'Baseline'].iloc[0]
    improvement_rmse = ((baseline_row['Test_RMSE'] - best_overall['Test_RMSE']) /
                        baseline_row['Test_RMSE'] * 100)
    improvement_nasa = ((baseline_row['Test_NASA'] - best_overall['Test_NASA']) /
                        baseline_row['Test_NASA'] * 100)

    f.write(f"\nImprovement over Baseline:\n")
    f.write(f"  RMSE: {improvement_rmse:+.2f}%\n")
    f.write(f"  NASA Score: {improvement_nasa:+.2f}%\n")

print("  Summary saved to 'results/ridge_regularization_summary.txt'")
print("\n" + "="*60)
```

```python
print(" Ridge regularization complete!")
print("="*60)
```

```
 Results saved to 'results/ridge_regularization_results.csv'
 Summary saved to 'results/ridge_regularization_summary.txt'

============================================================
 Ridge regularization complete!
============================================================
```

[ ]:

```python

```