```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import torch
import torch.nn as nn
from torch.utils.data import TensorDataset, DataLoader
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_absolute_error, r2_score

# Set device
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
print(f'Using device: {device}')
```

```
Using device: cuda
```

```python
data =
pd.read_csv("/kaggle/input/electricity-transformer-dataset/ETTm1.csv")

print(f"Dataset shape: {data.shape}")
print(f"Columns: {data.columns.tolist()}")
print(data.head())

data['date'] = pd.to_datetime(data['date'])
print(f"\nMissing values:\n{data.isnull().sum()}")
data.dropna(inplace=True)
```

```
Dataset shape: (69680, 8)
Columns: ['date', 'HUFL', 'HULL', 'MUFL', 'MULL', 'LUFL', 'LULL',
'OT']
                  date   HUFL   HULL   MUFL   MULL   LUFL   LULL
OT
0  2016-07-01 00:00:00  5.827  2.009  1.599  0.462  4.203  1.340
30.531000
1  2016-07-01 00:15:00  5.760  2.076  1.492  0.426  4.264  1.401
30.459999
2  2016-07-01 00:30:00  5.760  1.942  1.492  0.391  4.234  1.310
30.038000
3  2016-07-01 00:45:00  5.760  1.942  1.492  0.426  4.234  1.310
27.013000
4  2016-07-01 01:00:00  5.693  2.076  1.492  0.426  4.142  1.371
27.787001

Missing values:
date    0
HUFL    0
HULL    0
MUFL    0
MULL    0
LUFL    0
LULL    0
```

```
OT        0
dtype: int64
```

```python
# Extract time features
data['hour'] = data['date'].dt.hour
data['day_of_week'] = data['date'].dt.dayofweek
data['month'] = data['date'].dt.month

print(f"\nData after preprocessing: {data.shape}")
```

```
Data after preprocessing: (69680, 11)
```

```python
data_naive = data[['date', 'OT']].copy(deep=True)
data_naive['prev_OT'] = data_naive['OT'].shift(1)
data_naive.dropna(inplace=True)
data_naive['difference'] = data_naive['OT'] - data_naive['prev_OT']
data_naive['square_error'] = data_naive['difference'] ** 2

naive_mse = data_naive['square_error'].mean()
print(f'Naive Approach Mean Square Error: {naive_mse:.4f}')
```

```
Naive Approach Mean Square Error: 0.1984
```

```python
feature_columns = ['HUFL', 'HULL', 'MUFL', 'MULL', 'LUFL', 'LULL',
'OT']

input_data = data[feature_columns].copy()

# Hyperparameters
T = 96 #Sequence length
D = input_data.shape[1] #Input dimensions
N = len(input_data) - T #Total sequences

print(f"Sequence length (T): {T}")
print(f"Input dimensions (D): {D}")
print(f"Total sequences (N): {N}")
```

```
Sequence length (T): 96
Input dimensions (D): 7
Total sequences (N): 69584
```

```python
# Train/Val/Test split
train_size = int(len(input_data) * 0.70)
val_size = int(len(input_data) * 0.15)
test_size = N - train_size - val_size

print(f"\nTrain size: {train_size}")
print(f"Validation size: {val_size}")
print(f"Test size: {test_size}")
```

```
Train size: 48776
Validation size: 10452
Test size: 10356
```

```
# Fit scaler on training data only
scaler = StandardScaler()
scaler.fit(input_data[:train_size + T - 1])

# Transform all data using training statistics
input_data_scaled = scaler.transform(input_data)

print(f" Scaler fit on training data only (indices 0 to {train_size +
T - 1})")
```

```
 Scaler fit on training data only (indices 0 to 48871)
```

```
# Extract the index of OT column to scale targets consistently
ot_column_idx = feature_columns.index('OT')
# Get scaled OT values for targets
targets_scaled = input_data_scaled[:, ot_column_idx]

def create_sequences(data, targets, start_idx, end_idx, T):
    """Create input sequences and targets"""
    n_sequences = end_idx - start_idx
    X = np.zeros((n_sequences, T, data.shape[1]))
    y = np.zeros((n_sequences, 1))

    for i in range(n_sequences):
        t = i + start_idx
        X[i, :, :] = data[t:t+T]
        y[i] = targets[t+T]

    return X, y

# Create sequences
X_train, y_train = create_sequences(input_data_scaled, targets_scaled,
0, train_size, T)
X_val, y_val = create_sequences(input_data_scaled, targets_scaled,
train_size, train_size + val_size, T)
X_test, y_test = create_sequences(input_data_scaled, targets_scaled,
train_size + val_size, N, T)

# Convert to PyTorch tensors
X_train = torch.from_numpy(X_train.astype(np.float32))
y_train = torch.from_numpy(y_train.astype(np.float32))
X_val = torch.from_numpy(X_val.astype(np.float32))
y_val = torch.from_numpy(y_val.astype(np.float32))
X_test = torch.from_numpy(X_test.astype(np.float32))
y_test = torch.from_numpy(y_test.astype(np.float32))
```

```
print(f"Tensor shapes:")
print(f"X_train: {X_train.shape}, y_train: {y_train.shape}")
print(f"X_val: {X_val.shape}, y_val: {y_val.shape}")
print(f"X_test: {X_test.shape}, y_test: {y_test.shape}")
```

```
Tensor shapes:
X_train: torch.Size([48776, 96, 7]), y_train: torch.Size([48776, 1])
X_val: torch.Size([10452, 96, 7]), y_val: torch.Size([10452, 1])
X_test: torch.Size([10356, 96, 7]), y_test: torch.Size([10356, 1])
```

```
BATCH_SIZE = 64

train_dataset = TensorDataset(X_train, y_train)
val_dataset = TensorDataset(X_val, y_val)
test_dataset = TensorDataset(X_test, y_test)

train_loader = DataLoader(train_dataset, batch_size=BATCH_SIZE,
shuffle=True, drop_last=True)
val_loader = DataLoader(val_dataset, batch_size=BATCH_SIZE,
shuffle=False)
test_loader = DataLoader(test_dataset, batch_size=BATCH_SIZE,
shuffle=False)

print(f"\nBatch size: {BATCH_SIZE}")
print(f"Training batches per epoch: {len(train_loader)}")
```

```

Batch size: 64
Training batches per epoch: 762
```

```
class PositionalEncoding(nn.Module):
    """Adds positional information to the input embeddings"""
    def __init__(self, d_model, max_len=5000, dropout=0.1):
        super(PositionalEncoding, self).__init__()
        self.dropout = nn.Dropout(p=dropout)

        # Create positional encoding matrix
        pe = torch.zeros(max_len, d_model)
        position = torch.arange(0, max_len,
dtype=torch.float).unsqueeze(1)
        div_term = torch.exp(torch.arange(0, d_model, 2).float() * (-
np.log(10000.0) / d_model))

        pe[:, 0::2] = torch.sin(position * div_term)
        pe[:, 1::2] = torch.cos(position * div_term)
        pe = pe.unsqueeze(0)  # Add batch dimension

        self.register_buffer('pe', pe)

    def forward(self, x):
        # x shape: (batch_size, seq_len, d_model)
```

```
        x = x + self.pe[:, :x.size(1), :]
        return self.dropout(x)


class TransformerModel(nn.Module):
    """Transformer model for time series prediction"""
    def __init__(self, input_dim, d_model=128, nhead=8, num_layers=2,
                 dim_feedforward=512, dropout=0.2, output_dim=1):
        super(TransformerModel, self).__init__()

        # Input projection layer
        self.input_projection = nn.Linear(input_dim, d_model)

        # Positional encoding
        self.pos_encoder = PositionalEncoding(d_model,
dropout=dropout)

        # Transformer encoder layers
        encoder_layer = nn.TransformerEncoderLayer(
            d_model=d_model,
            nhead=nhead,
            dim_feedforward=dim_feedforward,
            dropout=dropout,
            batch_first=True  # Input shape: (batch, seq, feature)
        )
        self.transformer_encoder =
nn.TransformerEncoder(encoder_layer, num_layers=num_layers)

        # Output layer
        self.fc_out = nn.Linear(d_model, output_dim)

        self.d_model = d_model

    def forward(self, x):
        # x shape: (batch_size, seq_len, input_dim)

        # Project input to d_model dimensions
        x = self.input_projection(x)  # (batch, seq, d_model)

        # Add positional encoding
        x = self.pos_encoder(x)

        # Pass through transformer encoder
        x = self.transformer_encoder(x)  # (batch, seq, d_model)

        # Take the output from the last time step
        x = x[:, -1, :]  # (batch, d_model)

        # Final prediction
        output = self.fc_out(x)  # (batch, output_dim)
```

```python
        return output

# Model hyperparameters
d_model = 128          # Dimension of the model
nhead = 8              # Number of attention heads
num_layers = 2         # Number of transformer layers
dim_feedforward = 128  # Dimension of feedforward network
dropout = 0.2          # Dropout rate
output_dim = 1         # Single output (CGM prediction)

# Create model
model = TransformerModel(
    input_dim=D,
    d_model=d_model,
    nhead=nhead,
    num_layers=num_layers,
    dim_feedforward=dim_feedforward,
    dropout=dropout,
    output_dim=output_dim
)
model.to(device)

print(f"\nModel: {sum(p.numel() for p in model.parameters())}
parameters")
```

```
Model: 200321 parameters
```

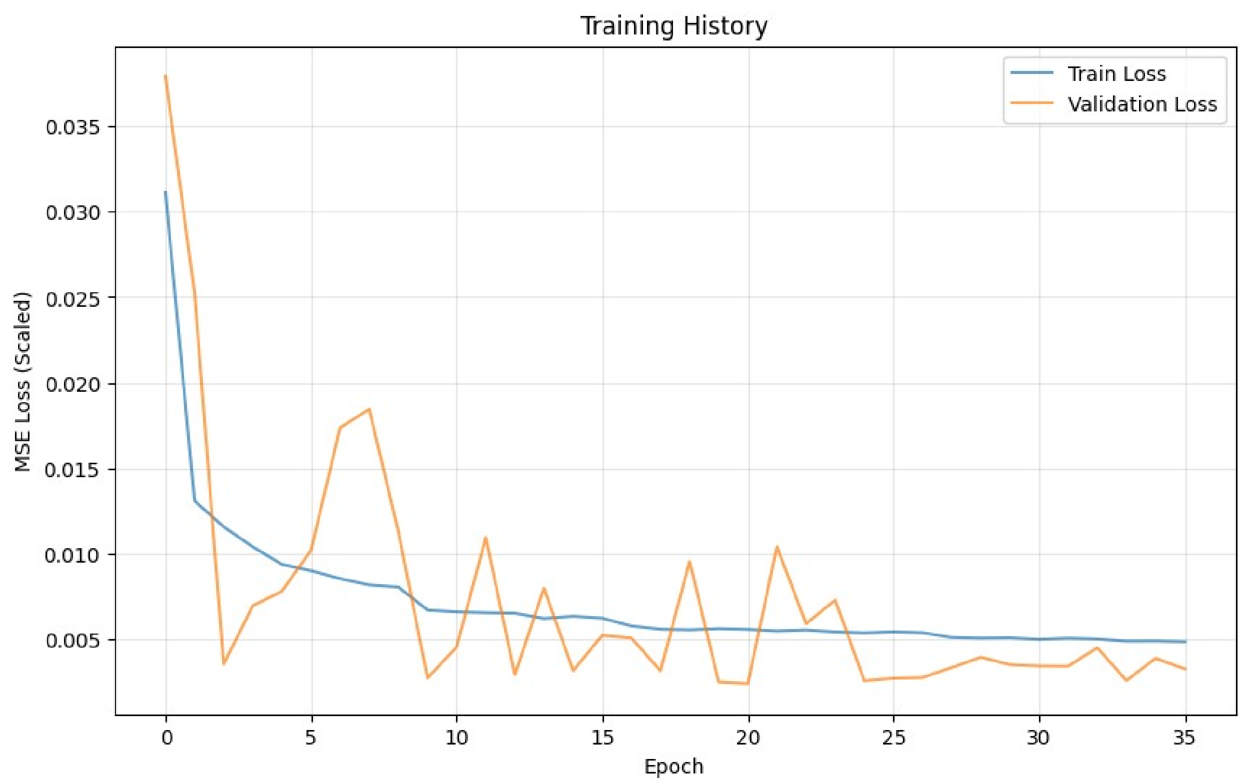
```python
def train(model, train_loader, val_loader, learning_rate=0.001,
epochs=100, patience=15):

    criterion = nn.MSELoss()
    optimizer = torch.optim.AdamW(model.parameters(),
lr=learning_rate, weight_decay=1e-5)
    scheduler = torch.optim.lr_scheduler.ReduceLROnPlateau(
        optimizer, mode='min', factor=0.5, patience=5
    )

    train_losses = []
    val_losses = []
    best_val_loss = float('inf')
    patience_counter = 0

    for epoch in range(epochs):
        # Training
        model.train()
        train_loss_batches = []

        for batch_X, batch_y in train_loader:
            batch_X, batch_y = batch_X.to(device), batch_y.to(device)
```

```
            optimizer.zero_grad()
            outputs = model(batch_X)
            loss = criterion(outputs, batch_y)

            loss.backward()
            torch.nn.utils.clip_grad_norm_(model.parameters(),
max_norm=1.0)
            optimizer.step()

            train_loss_batches.append(loss.item())

        avg_train_loss = np.mean(train_loss_batches)
        train_losses.append(avg_train_loss)

        # Validation
        model.eval()
        val_loss_batches = []

        with torch.no_grad():
            for batch_X, batch_y in val_loader:
                batch_X, batch_y = batch_X.to(device),
batch_y.to(device)
                outputs = model(batch_X)
                loss = criterion(outputs, batch_y)
                val_loss_batches.append(loss.item())

        avg_val_loss = np.mean(val_loss_batches)
        val_losses.append(avg_val_loss)

        scheduler.step(avg_val_loss)

        # Early stopping
        if avg_val_loss < best_val_loss:
            best_val_loss = avg_val_loss
            patience_counter = 0
            torch.save(model.state_dict(),
'best_transformer_model.pth')
        else:
            patience_counter += 1

        if (epoch + 1) % 5 == 0:
            print(f'Epoch {epoch+1}/{epochs} - Train Loss:
{avg_train_loss:.4f}, Val Loss: {avg_val_loss:.4f}')

        if patience_counter >= patience:
            print(f'\nEarly stopping at epoch {epoch+1}')
            break

    # Load best model
```

```python
    model.load_state_dict(torch.load('best_transformer_model.pth'))
    return train_losses, val_losses

train_losses, val_losses = train(
    model, train_loader, val_loader,
    learning_rate=0.001, epochs=100, patience=15
)
```

```
Epoch 5/100 - Train Loss: 0.0094, Val Loss: 0.0078
Epoch 10/100 - Train Loss: 0.0067, Val Loss: 0.0027
Epoch 15/100 - Train Loss: 0.0063, Val Loss: 0.0031
Epoch 20/100 - Train Loss: 0.0056, Val Loss: 0.0025
Epoch 25/100 - Train Loss: 0.0054, Val Loss: 0.0026
Epoch 30/100 - Train Loss: 0.0051, Val Loss: 0.0035
Epoch 35/100 - Train Loss: 0.0049, Val Loss: 0.0039

Early stopping at epoch 36
```

```python
# Plot
plt.figure(figsize=(10, 6))
plt.plot(train_losses, label='Train Loss', alpha=0.7)
plt.plot(val_losses, label='Validation Loss', alpha=0.7)
plt.xlabel('Epoch')
plt.ylabel('MSE Loss (Scaled)')
plt.title('Training History')
plt.legend()
plt.grid(True, alpha=0.3)
plt.show()
```

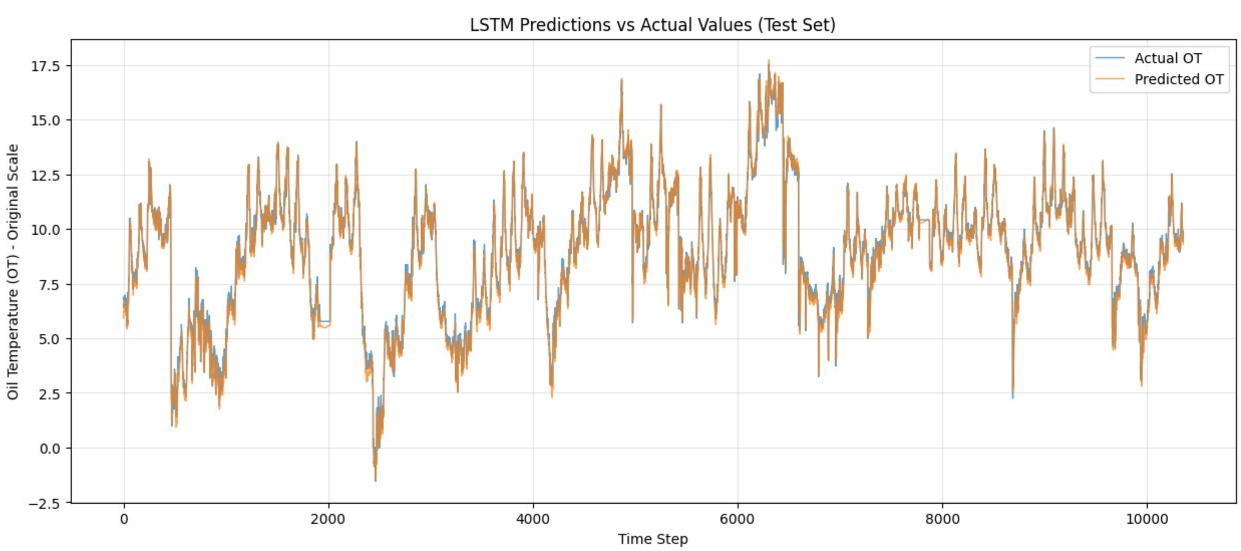



```
model.eval()
test_predictions_scaled = []
test_targets_scaled = []

with torch.no_grad():
    for batch_X, batch_y in test_loader:
        batch_X = batch_X.to(device)
        outputs = model(batch_X)

test_predictions_scaled.extend(outputs.cpu().numpy().flatten())
        test_targets_scaled.extend(batch_y.numpy().flatten())

test_predictions_scaled = np.array(test_predictions_scaled)
test_targets_scaled = np.array(test_targets_scaled)

# Get scaler parameters for OT column
ot_mean = scaler.mean_[ot_column_idx]
ot_std = scaler.scale_[ot_column_idx]

# Inverse transform: original = scaled * std + mean
test_predictions = test_predictions_scaled * ot_std + ot_mean
test_targets = test_targets_scaled * ot_std + ot_mean

print(f"Predictions and targets converted to original scale")

# Calculate metrics on ORIGINAL scale
```

```
mse = np.mean((test_targets - test_predictions) ** 2)
rmse = np.sqrt(mse)
mae = np.mean(np.abs(test_targets - test_predictions))
r2   = r2_score(test_targets, test_predictions)

print(f"  MSE:  {mse:.4f}")
print(f"  RMSE: {rmse:.4f}")
print(f"  MAE:  {mae:.4f}")
print(f"  R2:  {r2:.4f}")
```

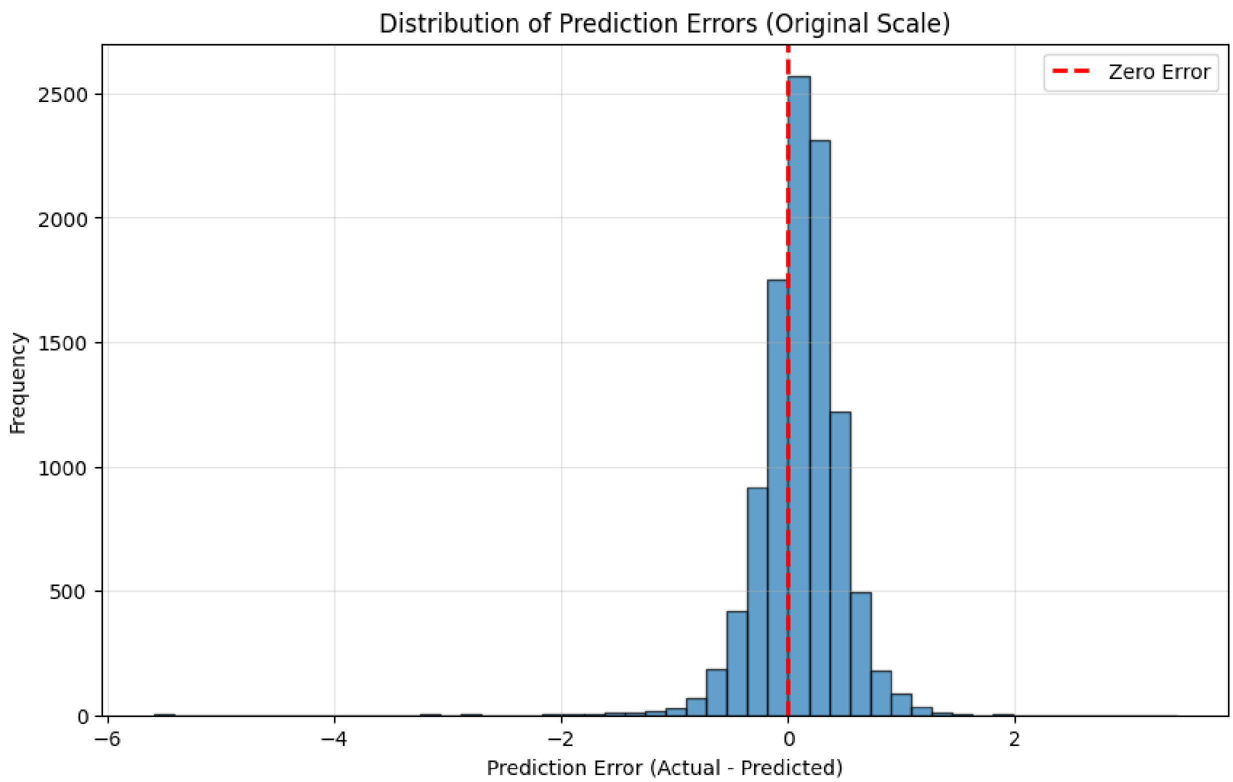
```
Predictions and targets converted to original scale
  MSE:  0.1501
  RMSE: 0.3874
  MAE:  0.2796
  R2:  0.9814
```

```
plt.figure(figsize=(15, 6))
plot_samples = min( len(test_predictions), len(test_predictions))
plt.plot(test_targets[:plot_samples], label='Actual OT', linewidth=1,
alpha=0.7)
plt.plot(test_predictions[:plot_samples], label='Predicted OT',
linewidth=1, alpha=0.7)
plt.xlabel('Time Step')
plt.ylabel('Oil Temperature (OT) - Original Scale')
plt.title('LSTM Predictions vs Actual Values (Test Set)')
plt.legend()
plt.grid(True, alpha=0.3)
plt.show()
```

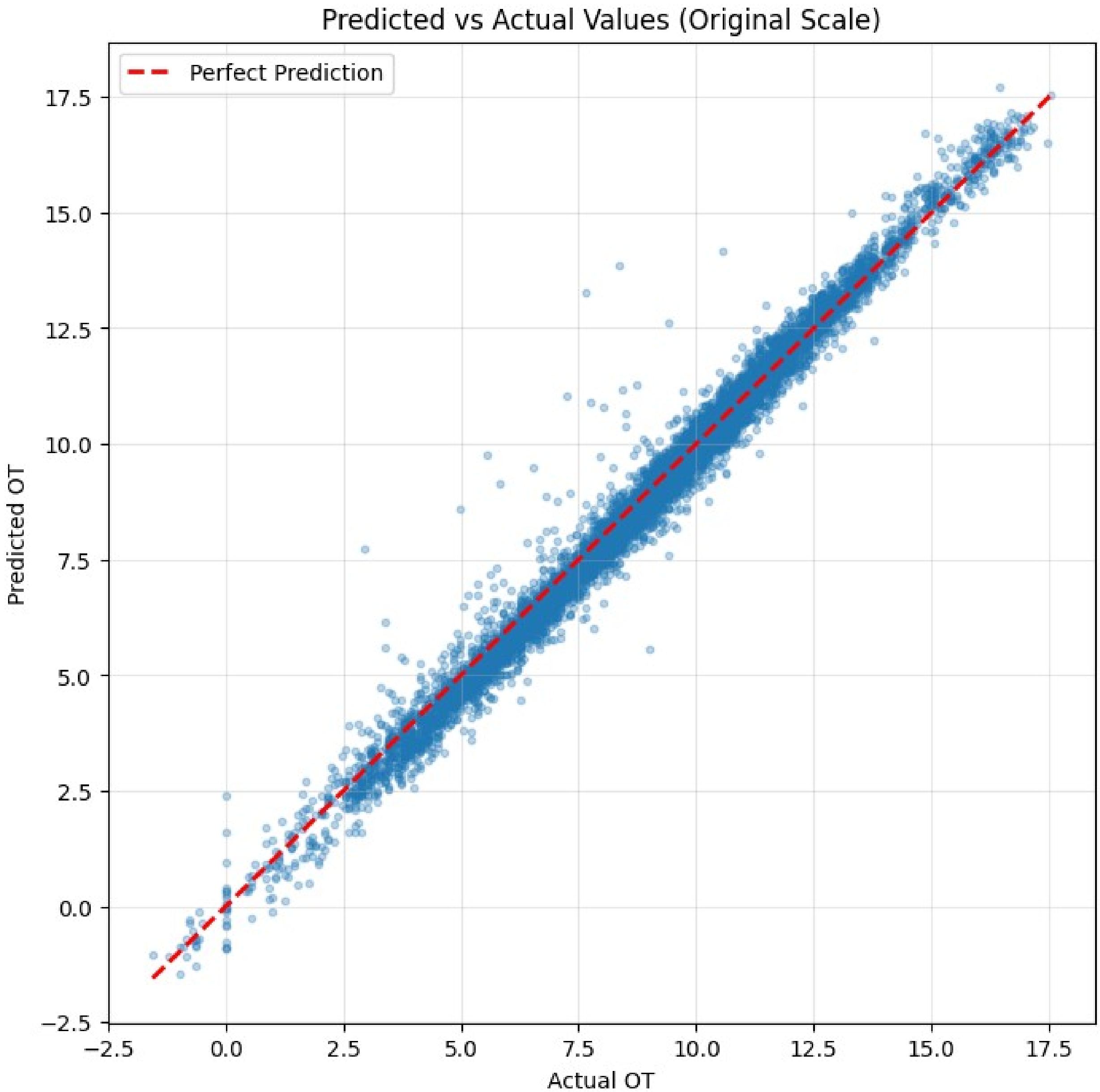



```
errors = test_targets - test_predictions
plt.figure(figsize=(10, 6))
plt.hist(errors, bins=50, edgecolor='black', alpha=0.7)
```

```
plt.xlabel('Prediction Error (Actual - Predicted)')
plt.ylabel('Frequency')
plt.title('Distribution of Prediction Errors (Original Scale)')
plt.axvline(x=0, color='r', linestyle='--', linewidth=2, label='Zero
Error')
plt.legend()
plt.grid(True, alpha=0.3)
plt.show()
```




```
plt.figure(figsize=(8, 8))
plt.scatter(test_targets, test_predictions, alpha=0.3, s=10)
plt.plot([test_targets.min(), test_targets.max()],
         [test_targets.min(), test_targets.max()],
         'r--', linewidth=2, label='Perfect Prediction')
plt.xlabel('Actual OT')
plt.ylabel('Predicted OT')
plt.title('Predicted vs Actual Values (Original Scale)')
plt.legend()
plt.grid(True, alpha=0.3)
plt.show()
```



Predicted vs Actual Values (Original Scale)
Perfect Prediction
Predicted OT
Actual OT
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
−2.5
−2.5
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5