1. 数据预处理

In [1]:
```python
import numpy as np
import scipy.io
from datetime import datetime
import matplotlib.pyplot as plt
%matplotlib inline
```

1.1 数据读取函数定义

注： mat 文件数据结构见 BatteryDataset 下的 txt 文件

In [2]:
```python
def TimeConvert(hmm):
    """
        转换时间格式，将字符串转换成 datatime 格式
    Args:
        hmm: 待输入的原始时间数据 (ndarray)
    Returns:
        标准化后的时间数据
    """
    year, month, day, hour, minute, second = \
                int(hmm[0]), int(hmm[1]), int(hmm[2]), \
                int(hmm[3]), int(hmm[4]), int(hmm[5])
    return datetime(year=year, month=month, day=day,
                    hour=hour, minute=minute, second=second)

def LoadMat(mat_file):
    """
        加载 mat 文件数据
    Args:
        mat_file: 待加载的文件路径 (string)
    Returns:
        读取的数据 (list)，其中每个元素为一个嵌套的 dict 类型
    """
    # 函数返回一个字典，其中键是 mat 文件中变量的名称，值是对应的数据数组
    data = scipy.io.loadmat(mat_file)
    # 从文件路径中提取文件名(不包含扩展名),用于访问字典的值
    fileName = mat_file.split('/')[-1].split('.')[0]
    col = data[fileName] # 获取整个数据(一个(1 x N)的四层结构化数组)
    col = col[0][0][0][0] # 去除冗余维度，访问包含所有循环数据的(616,)结构化数组
    size = col.shape[0] # 获取数组的大小(cycle 的数量)
    # print("data['B0005'].dtype:",data['B0005'].dtype,"value:",data['B0005'])
```

```python
    # print("data['B0005'][0][0][0][0].dtype:",data['B0005'][0][0][0][0].dtype,
    #       "value:",data['B0005'][0][0][0][0])
    # print("data['B0005'][0][0][0][0][0][3][0].dtype:",data['B0005'][0][0][0][0][0][3][0].dtype,
    #       "value:",data['B0005'][0][0][0][0][0][3][0])

    data = []
    for i in range(size): # 遍历每个 cycle 的数据
        """ dtype.fields 方法用于访问 NumPy 结构化数组的字段信息，它返回一个字典，其中：
        键：是结构化数组中每个字段的名称（字符串）；
        值：是描述每个字段的元组，包含字段的数据类型、字节偏移量以及可选的标题。 """
        k = list(col[i][3][0].dtype.fields.keys()) # 获取结构化数组(data 字段)中所有子字段名称的列表
        d1, d2 = {}, {}
        if str(col[i][0][0]) != 'impedance': # 去除 impedance 类型的数据
            for j in range(len(k)): # 遍历(data 字段)数组中的每个子字段
                t = col[i][3][0][0][j][0] # 获取该字段的数组数据
                l = [t[m] for m in range(len(t))] # 遍历提取数组中每个数据转为列表
                d2[k[j]] = l # 保存该数据及其对应的字段名称(以键值对的形式存在)
        # 将每个样本(cycle)的类型、温度、时间和数据存储到字典 d1 中
        d1['type'], d1['temp'], d1['time'], d1['data'] = \
            str(col[i][0][0]), int(col[i][1][0]), str(TimeConvert(col[i][2][0])), d2
        data.append(d1)

    return data

def GetBatteryCapacity(Battery):
    """
        获取单个锂电池的容量数据
    Args:
        Battery: 单个电池的数据 (dict)
    Returns:
        获取的电池容量数据 (list)，包含两个元素，第一个为放电周期，第二个为容量数据
    """
    cycle, capacity = [], []
    i = 1
    for Bat in Battery:
        if Bat['type'] == 'discharge': # 放电状态下获取容量数据
            capacity.append(Bat['data']['Capacity'][0])
            cycle.append(i)
            i += 1
    return [cycle, capacity]

def GetBatteryValues(Battery, Type='charge'):
    """
        获取单个锂电池充电或放电时的测试数据(默认为充电状态的数据)
    Args:
        Battery: 单个电池的数据 (dict)
```

```
        Type: 指定要读取的数据类型 (string)
    Returns:
        获取的电池数据， list 类型
    """
    data = []
    for Bat in Battery:
        if Bat['type'] == Type:
            data.append(Bat['data'])
    return data
```

In [3]:
```
# 用于测试数据
# Battery_list = 'B0005'
# dir_path = r'BatteryDataset/'

# path = dir_path + Battery_list + '.mat'
# data = LoadMat(path)
```

1.2 读取数据

In [4]:
```
Battery_list = ['B0005', 'B0006', 'B0007', 'B0018']
dir_path = r'BatteryDataset/'

capacity, charge, discharge = {}, {}, {}
for name in Battery_list:
    print('Loading Dataset ' + name + '.mat ...')
    path = dir_path + name + '.mat'
    data = LoadMat(path)
    capacity[name] = GetBatteryCapacity(data) # 放电时的容量数据
    charge[name] = GetBatteryValues(data, 'charge') # 充电数据
    discharge[name] = GetBatteryValues(data, 'discharge') # 放电数据
```

```
Loading Dataset B0005.mat ...
Loading Dataset B0006.mat ...
Loading Dataset B0007.mat ...
Loading Dataset B0018.mat ...
```

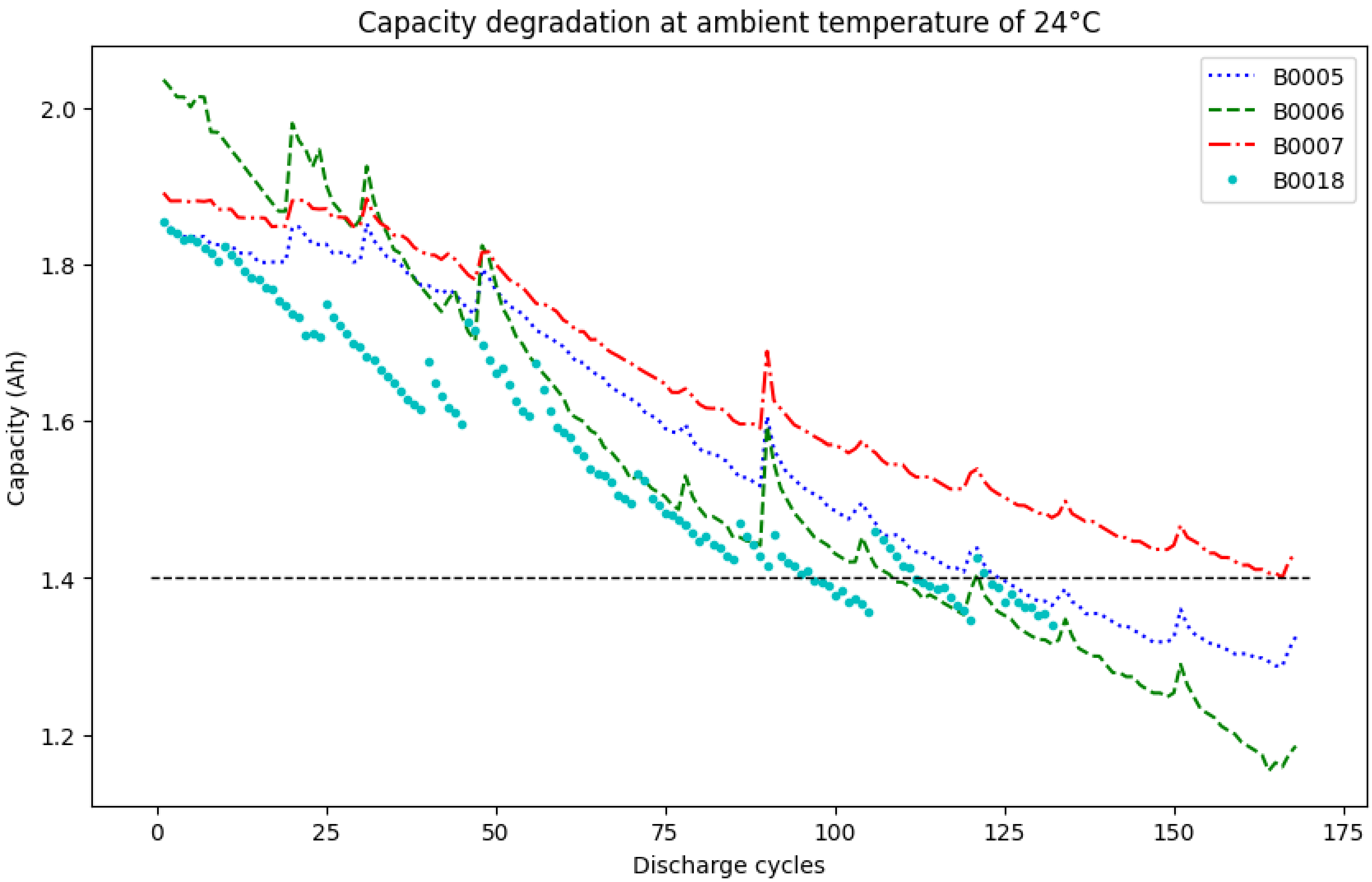
1.3 数据展示

1.3.1 不同电池容量 vs. 充放电周期曲线

In [5]:
```
fig, ax = plt.subplots(1, figsize=(10, 6))
color_list = ['b:', 'g--', 'r-.', 'c.']
c = 0
for name,color in zip(Battery_list, color_list):
```

```
    df_result = capacity[name]
    ax.plot(df_result[0], df_result[1], color, label=name)
# 临界点直线(电池容量下降30%则认为报废)
plt.plot([-1,170],[2.0*0.7,2.0*0.7],c='black',lw=1,ls='--')
ax.set(xlabel='Discharge cycles', ylabel='Capacity (Ah)',
       title='Capacity degradation at ambient temperature of 24°C')
plt.legend()
```

Out[5]: <matplotlib.legend.Legend at 0x7fc6e6239130>



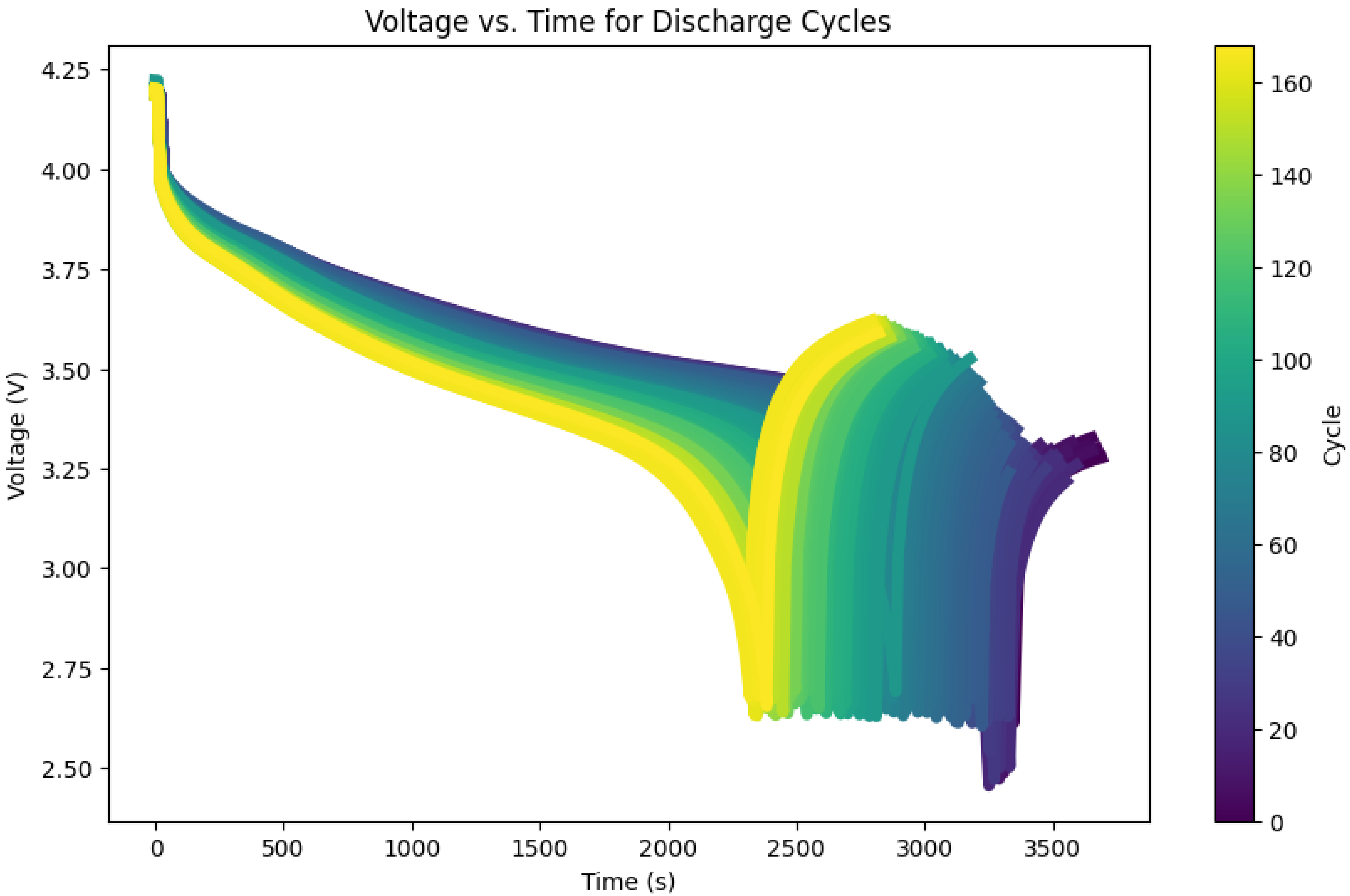
1.3.2 不同放电周期下，B0005号电池电压 vs. 放电周期曲线

In [6]:
```python
fig, ax = plt.subplots(1, figsize=(10, 6))
cmap = plt.get_cmap('viridis') # 选择合适的颜色映射, 'hsv', 'jet', 'viridis' 等

name = 'B0005' # 仅绘制第 B0005 号电池
for i, cycle_data in enumerate(discharge[name]):
    # 使用 plot 绘制，并根据循环次数着色
    ax.plot(cycle_data['Time'], cycle_data['Voltage_measured'],
            c=cmap(i / len(discharge[name])), linewidth=5.0)
# 添加颜色条
sm = plt.cm.ScalarMappable(cmap=cmap,
                           norm=plt.Normalize(vmin=0, vmax=len(discharge[name])))
sm.set_array([])  # 这是为了让colorbar工作，即使没有明确的映射数组
cbar = plt.colorbar(sm, ax=ax)
cbar.set_label('Cycle') # 添加颜色条标签

ax.set(xlabel='Time (s)', ylabel='Voltage (V)',
       title='Voltage vs. Time for Discharge Cycles')
```

Out[6]:
```
[Text(0.5, 0, 'Time (s)'),
 Text(0, 0.5, 'Voltage (V)'),
 Text(0.5, 1.0, 'Voltage vs. Time for Discharge Cycles')]
```



1.3.3 不同放电周期下，B0005号电池电流 vs. 充电周期曲线

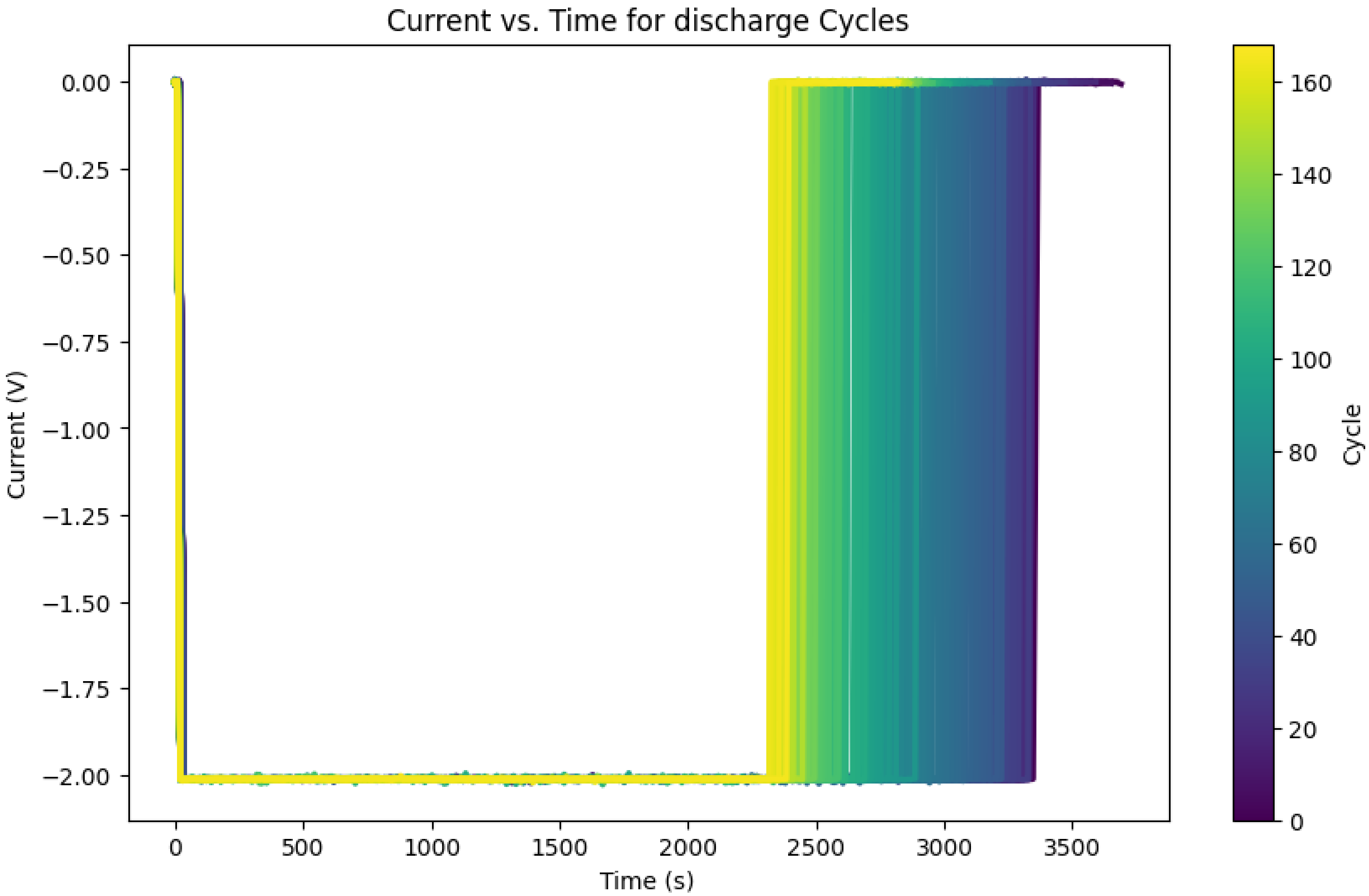
In [7]:
```
fig, ax = plt.subplots(1, figsize=(10, 6))
cmap = plt.get_cmap('viridis') # 选择合适的颜色映射, 'hsv', 'jet', 'viridis' 等

name = 'B0005' # 仅绘制第 B0005 号电池
for i, cycle_data in enumerate(discharge[name]):
    # 使用 plot 绘制, 并根据循环次数着色
    ax.plot(cycle_data['Time'], cycle_data['Current_measured'],
            c=cmap(i / len(charge[name])), linewidth=2.5)
# 添加颜色条
sm = plt.cm.ScalarMappable(cmap=cmap,
```

```python
                        norm=plt.Normalize(vmin=0, vmax=len(discharge[name])))
sm.set_array([])  # 这是为了让colorbar工作，即使没有明确的映射数组
cbar = plt.colorbar(sm, ax=ax)
cbar.set_label('Cycle') # 添加颜色条标签

ax.set(xlabel='Time (s)', ylabel='Current (V)',
       title='Current vs. Time for discharge Cycles')
```

Out[7]:
```
[Text(0.5, 0, 'Time (s)'),
 Text(0, 0.5, 'Current (V)'),
 Text(0.5, 1.0, 'Current vs. Time for discharge Cycles')]
```



1.4 创建数据集

1.4.1 数据集类定义

In [8]:

```python
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torch.utils.data import Dataset, DataLoader, Subset, ConcatDataset
from sklearn.metrics import mean_squared_error
from math import sqrt
import random
import os
# 注册设备
device = "cuda" if torch.cuda.is_available() else "cpu"
```

In [9]:

```python
# 定义数据集类
class TimeSeriesDataset(Dataset):
    def __init__(self, data, window_size):
        self.window_size = window_size
        self.data = torch.tensor(data, dtype=torch.float32).to(device)
        # 计算最大索引
        self.max_index = self.data.shape[0] - self.window_size - 1

    def __len__(self):
        return self.max_index + 1 #  返回有效数据长度

    def __getitem__(self, index):
        if index > self.max_index:
            raise IndexError(f"Index {index} is out of bounds."
                             f"Max index is {self.max_index}")
        x = self.data[index:index + self.window_size]
        y = self.data[index + self.window_size]
        return x.unsqueeze(1), y.unsqueeze(0) # 添加一个特征维度
```

1.4.2 数据集获取函数定义

In [10]:

```python
def get_split_dataset(data_dict, name, window_size=8, shuffle=True,
             capacity_threshold=0.0, train_ratio=0.0, batch_size=32):
    """
        获取分割后的训练集和测试集 DataLoader
    Args:
        data_dict: 字典类型，键为电池名称，值为包含电池信息的元组，
                其中第二个元素是容量数据列表 (list)
        name: 指定为测试集的电池数据名称 (str)
        window_size: 用于创建时间序列的窗口大小 (int)
```

```python
        shuffle: 是否打乱训练集 (bool)
        train_ratio: 用于训练数据划分的比例 (float32)
        capacity_threshold: 用于训练数据划分的阈值 (float32)
        batch_size: 训练的批大小 (int)
    Returns:
        包含训练数据和测试数据 DataLoader 的元组。
    """
    data = data_dict[name][1]
    # 创建数据集
    dataset = TimeSeriesDataset(data, window_size)
    # 划分数据集
    if capacity_threshold > 0: # 优先使用阈值前的数据训练，阈值后的数据测试
        max_capacity = max(data)
        capacity = max_capacity * capacity_threshold
        point = next((i for i, val in enumerate(data) if val < capacity), None)
    else: # 否则按照指定的比例进行划分
        if (0 < train_ratio <= 1):
            point = int(len(data) * train_ratio)
        else:
            raise ValueError("Train ratio must be between 0 and 1.")
    # 使用 Subset 创建训练集和验证集，保持时间顺序
    train_dataset = Subset(dataset, range(point))
    test_dataset = Subset(dataset, range(point, len(dataset)))

    # 创建 DataLoader
    train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=shuffle)
    test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False)

    return train_loader, test_loader

def get_data(data_dict, name, window_size=8, shuffle=True, batch_size=32):
    """
        留一法获取训练集和测试集 DataLoader,每次留一个电池的数据作为测试集
    Args:
        data_dict: 字典类型，键为电池名称，值为包含电池信息的元组，
                   其中第二个元素是容量数据列表 (list)
        name: 指定为测试集的电池数据名称 (str)
        window_size: 用于创建时间序列的窗口大小 (int)
        shuffle: 是否打乱训练集 (bool)
        batch_size: 训练的批大小 (int)
    Returns:
        包含训练数据和测试数据 DataLoader 的元组。
    """
    test_data = data_dict[name][1]
    test_dataset = TimeSeriesDataset(test_data, window_size)
```

```python
    train_datasets = []
    for k, v in data_dict.items():
        if k != name:
            dataset = TimeSeriesDataset(v[1], window_size)
            train_datasets.append(dataset)
    train_dataset = ConcatDataset(train_datasets) # 使用 ConcatDataset 拼接多个数据集

    # 创建 DataLoader
    train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=shuffle)
    test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False)

    # 打印 DataLoader
    # print("train_loader_num:", len(train_loader.dataset))
    # print("test_loader_num:", len(test_loader.dataset))
    # for x, y in train_loader:
    #     print("x:", x.shape) # 输出: x: (batch_size, window_size, num_features)
    #     print("y:", y.shape) # 输出: y: (batch_size, 1)
    #     break
    return train_loader, test_loader
```

In [11]:
```python
# window_size = 8
# for i in range(len(Battery_list)):
#     name = Battery_list[i]
#     get_data(capacity, name, window_size)
```

2. 模型建立

In [12]:
```python
# 定义CNN层
class CNNLayer(nn.Module):
    def __init__(self, num_channels, out_dim, kernel_size=1):
        super(CNNLayer, self).__init__()
        self.conv1 = nn.Conv1d(in_channels=num_channels,
                               out_channels=out_dim,
                               kernel_size=kernel_size)

    def forward(self, x):
        x = F.relu(self.conv1(x)) # x.shape([batch_size, out_dim, 1])
        return x

# 定义LSTM层
class LSTMLayer(nn.Module):
    def __init__(self, input_dim, hidden_dim, num_layers, bidirectional):
        super(LSTMLayer, self).__init__()
        self.hidden_size = hidden_dim
```

```python
        self.num_layers = num_layers
        self.bidirectional = bidirectional
        self.lstm = nn.LSTM(input_size=input_dim, hidden_size=hidden_dim,
                            num_layers=num_layers, batch_first=True,
                            bidirectional=bidirectional)

    def forward(self, x):
        h0 = torch.zeros(self.num_layers*2 if self.bidirectional else
                         self.num_layers, x.size(0),
                         self.hidden_size).to(device) # 初始化隐藏状态h0
        c0 = torch.zeros(self.num_layers*2 if self.bidirectional else
                         self.num_layers, x.size(0),
                         self.hidden_size).to(device)  # 初始化记忆状态c0
        output, (hidden, cell) = self.lstm(x, (h0, c0))
        # output.shape([batch_size, 1, hidden_dim*2 if bidirectional else hidden_dim])
        return output

# 定义Attention层
class AttentionLayer(nn.Module):
    def __init__(self, feature_dim, step_dim):
        super(AttentionLayer, self).__init__()
        self.attention = nn.Linear(feature_dim, step_dim)
        self.context_vector = nn.Linear(step_dim, 1, bias=False)

    def forward(self, x):
        # 将输出值限制在 -1 到 1 之间, shape: [batch_size, feature_dim, step_dim]
        attention_weights = torch.tanh(self.attention(x))
        # 为每个时间步计算一个未归一化的注意力权重, shape: [batch_size, 1]
        attention_weights = self.context_vector(attention_weights).squeeze(2)
        attention_weights = F.softmax(attention_weights, dim=1) # 对权重归一化
        # 将注意力权重与输入 x 相乘, shape: [batch_size, feature_dim]
        context_vector = torch.bmm(attention_weights.unsqueeze(1), x).squeeze(1)
        return context_vector, attention_weights

# 建立组合模型 CNN-LSTM-Attention
class CLAM(nn.Module):
    def __init__(self, num_channels, out_dim, feature_dim, kernel_size, hidden_dim,
                 num_layers, bidirectional, step_dim, output_dim):
        super(CLAM, self).__init__()
        self.cnn = CNNLayer(num_channels, out_dim, kernel_size)
        self.lstm = LSTMLayer(out_dim, hidden_dim,
                              num_layers, bidirectional)
        self.attention = AttentionLayer(hidden_dim * 2 if bidirectional else
                                        hidden_dim, step_dim)
        self.fc = nn.Linear(hidden_dim * 2 if bidirectional else hidden_dim, output_dim)
```

```
    def forward(self, x):
        x = x.transpose(1, 2) # 交换维度
        x = self.cnn(x)
        x = x.transpose(1, 2)
        x = self.lstm(x)
        x, _ = self.attention(x)
        x = self.fc(x)
        # x = self.fc(x[:, -1, :]) # 取序列最后一个时间步的输出作为预测
        return x
```

3. 模型训练

3.1 训练函数定义

3.1.1 模型获取函数和批训练函数定义

In [13]:
```
def get_model(num_channels, out_dim, feature_dim, kernel_size, hidden_dim,
              num_layers, bidirectional, step_dim, output_dim):
    """
        获取模型，并指定优化器和损失计算方法
    Args:
        num_channels: 输入模型的通道数，即窗口大小
        out_dim: 卷积的输出特征维度
        feature_dim: 输入数据的特征维度
        kernel_size: 卷积核大小
        hidden_dim: LSTM隐藏状态维度
        num_layers: LSTM层的数目
        bidirectional: 是否使用双向LSTM
        step_dim: 时间步维度
        output_dim: 输出维度(预测目标维度)
    Returns:
        指定的模型、损失函数和优化器的元组
    """
    model = CLAM(num_channels, out_dim, feature_dim, kernel_size, hidden_dim,
                 num_layers, bidirectional, step_dim, output_dim)
    loss_fn = nn.MSELoss() # 使用均方误差
    optimizer = optim.Adam(model.parameters(),
                           lr=0.001, betas=(0.5,0.999)) # 使用Adam优化器
    return model, loss_fn, optimizer


def train_batch(x, y, model, optimizer, loss_fn):
    """
```

```
        批训练函数
    Args:
        x: 输入的训练数据
        y: 输入的真实目标数据
        model: 指定的模型
        optimizer: 指定的优化器
        loss_fn: 指定的损失函数
    Returns:
        计算的损失标量
    """
    model.train() # 设置为训练
    prediction = model(x) # 输入数据
    # print("Prediction shape:", prediction.shape)
    batch_loss = loss_fn(prediction, y) # 计算损失
    batch_loss.backward() # 进行反向传播
    optimizer.step() # 梯度下降
    optimizer.zero_grad() # 清空梯度
    return batch_loss.item()
```

3.1.2 评估函数定义

In [14]:
```
def relative_error(y_test, y_predict, threshold):
    """
        计算预测值与真实值之间在达到特定阈值时的相对误差
    Args:
        y_test: 真实的电池容量衰减数据
        y_predict: 模型预测的电池容量衰减数据
        threshold: 定义电池寿命结束的容量阈值
    Returns:
        计算的相对误差分数
    """
    true_re, pred_re = len(y_test), 0

    for i in range(len(y_test) - 1):
        if y_test[i] <= threshold >= y_test[i+1]:
            true_re = i - 1 # 第一个下降到阈值前的数据的放电次数
            break
    for i in range(len(y_predict) - 1):
        if y_predict[i] <= threshold:
            pred_re = i - 1 # 预测的次数
            break
    # 计算相对误差，公式为 |真实剩余寿命 - 预测剩余寿命| / 真实剩余寿命
    score = abs(true_re - pred_re) / true_re
    if score > 1: score = 1
```

```
    return score


def evaluation(y_test, y_predict):
    """
        计算模型的评价指标：均方误差和均方根误差
    Args:
        y_test: 真实的电池容量衰减数据
        y_predict: 模型预测的电池容量衰减数据
    Returns:
        计算的均方误差和均方根误差
    """
    mse = mean_squared_error(y_test, y_predict)
    rmse = sqrt(mean_squared_error(y_test, y_predict))
    return mse, rmse

def setup_seed(seed):
    """
        设置环境的随机种子，保证训练结果的一致性
    Args:
        seed: 指定的随机种子
    Returns:
        None.
    """
    np.random.seed(seed) # 设置 NumPy 模块的随机种子
    random.seed(seed) # 设置 Python 内置 random 模块的随机种子
    os.environ['PYTHONHASHSEED'] = str(seed) # 设置 Python 的哈希种子
    torch.manual_seed(seed) # 设置 PyTorch 的随机种子
    if torch.cuda.is_available():
        torch.cuda.manual_seed(seed) # 为当前 GPU 设置随机种子
        torch.cuda.manual_seed_all(seed) # 为所有可用的 GPU 设置随机种子
        torch.backends.cudnn.benchmark = False # 禁用 cuDNN 的 benchmark 模式
        torch.backends.cudnn.deterministic = True # 启用 cuDNN 的确定性模式
```

3.2 开始训练

In [15]:
```
window_size = 16
out_dim = 32
feature_dim = 1
kernel_size = 3
hidden_dim = 64
num_layers = 2
bidirectional = True
step_dim = 16
output_dim = 1
```

```python
Rated_Capacity = 2.0 # 额定容量
epochs = 200 # 训练次数
seed = 42 # 随机种子
metric = 'rmse' # 评估指标

model, loss_fn, optimizer = get_model(feature_dim, out_dim, feature_dim,
                                      kernel_size, hidden_dim, num_layers,
                                      bidirectional, step_dim, output_dim)
setup_seed(seed) # 设置种子

score_list, result_list = [], []
for i in range(len(Battery_list)):
    name = Battery_list[i]
    train_loader, test_loader = get_data(capacity, name, window_size)
    model = model.to(device) # 注册模型到设备

    train_loss = [0]
    rmse, re = 1, 1
    score, best_score = float(1), float(1)
    best_pred = []
    for epoch in range(epochs):
        train_epoch_loss = []
        model.train()  # 设置为训练模式
        for index, batch in enumerate(iter(train_loader)):
            x, y = batch
            # 归一化
            x /= torch.tensor(Rated_Capacity).to(device)
            y /= torch.tensor(Rated_Capacity).to(device)
            batch_loss = train_batch(x, y, model, optimizer, loss_fn)
            train_epoch_loss.append(batch_loss)

        train_epoch_loss = np.array(train_epoch_loss).mean()
        train_loss.append(train_epoch_loss)

        if (epoch + 1) % 10 == 0:
            model.eval() # 设置为验证模式
            tesy_pred, test_y = [], []
            with torch.no_grad():
                for index, batch in enumerate(iter(test_loader)):
                    x, y = batch
                    # 归一化
                    x /= torch.tensor(Rated_Capacity).to(device)
                    y /= torch.tensor(Rated_Capacity).to(device)
                    pred = model(x)
```

```
                # 将预测值和真实值转换为 NumPy 数组并展平
                pred_np = (pred * Rated_Capacity).cpu().numpy().flatten()
                y_np = (y * Rated_Capacity).cpu().numpy().flatten()
                tesy_pred.extend(pred_np)
                test_y.extend(y_np)
        mse, rmse = evaluation(np.array(test_y), np.array(tesy_pred))
        re = relative_error(np.array(test_y),
                            np.array(tesy_pred), Rated_Capacity * 0.7)
        print(f"Epoch {epoch+1}/{epochs} Train Loss: {train_epoch_loss:.4f}",
              f"RMSE: {rmse:.4f} RE: {re:.4f}")

    # 使用验证集分数进行早停和模型选择
    score = re if metric == 're' else rmse
    if (batch_loss < 1e-4) and (score < best_score):
        best_score = score
        best_pred = tesy_pred
        # break

score_list.append(best_score)
result_list.append(list(tesy_pred))
print("score_list for 4 types of batteries:\n", np.array(score_list))
print(metric + ': for this seed: {:<6.4f}'.format(np.mean(np.array(score_list))))
print('------------------------------------------------------------------')
```

```
Epoch 10/200 Train Loss: 0.0006 RMSE: 0.0733 RE: 0.1495
Epoch 20/200 Train Loss: 0.0006 RMSE: 0.1046 RE: 0.2150
Epoch 30/200 Train Loss: 0.0008 RMSE: 0.0392 RE: 0.1028
Epoch 40/200 Train Loss: 0.0007 RMSE: 0.0715 RE: 0.1495
Epoch 50/200 Train Loss: 0.0006 RMSE: 0.0741 RE: 0.1495
Epoch 60/200 Train Loss: 0.0005 RMSE: 0.0269 RE: 0.0467
Epoch 70/200 Train Loss: 0.0003 RMSE: 0.0263 RE: 0.0467
Epoch 80/200 Train Loss: 0.0003 RMSE: 0.0278 RE: 0.0467
Epoch 90/200 Train Loss: 0.0004 RMSE: 0.0425 RE: 0.0841
Epoch 100/200 Train Loss: 0.0005 RMSE: 0.0234 RE: 0.0280
Epoch 110/200 Train Loss: 0.0003 RMSE: 0.0210 RE: 0.0000
Epoch 120/200 Train Loss: 0.0026 RMSE: 0.0293 RE: 0.0280
Epoch 130/200 Train Loss: 0.0003 RMSE: 0.0255 RE: 0.0374
Epoch 140/200 Train Loss: 0.0003 RMSE: 0.0288 RE: 0.0561
Epoch 150/200 Train Loss: 0.0003 RMSE: 0.0372 RE: 0.0748
Epoch 160/200 Train Loss: 0.0003 RMSE: 0.0631 RE: 0.1308
Epoch 170/200 Train Loss: 0.0003 RMSE: 0.0510 RE: 0.1028
Epoch 180/200 Train Loss: 0.0003 RMSE: 0.0455 RE: 0.0935
Epoch 190/200 Train Loss: 0.0003 RMSE: 0.0408 RE: 0.0841
Epoch 200/200 Train Loss: 0.0002 RMSE: 0.0187 RE: 0.0187
score_list for 4 types of batteries:
 [0.02101864]
rmse: for this seed: 0.0210
------------------------------------------------------------------
Epoch 10/200 Train Loss: 0.0006 RMSE: 0.0313 RE: 0.0330
Epoch 20/200 Train Loss: 0.0002 RMSE: 0.0344 RE: 0.0440
Epoch 30/200 Train Loss: 0.0002 RMSE: 0.0308 RE: 0.0330
Epoch 40/200 Train Loss: 0.0002 RMSE: 0.0337 RE: 0.0110
Epoch 50/200 Train Loss: 0.0002 RMSE: 0.0367 RE: 0.0549
Epoch 60/200 Train Loss: 0.0002 RMSE: 0.0329 RE: 0.0110
Epoch 70/200 Train Loss: 0.0003 RMSE: 0.0854 RE: 0.2308
Epoch 80/200 Train Loss: 0.0002 RMSE: 0.0290 RE: 0.0110
Epoch 90/200 Train Loss: 0.0001 RMSE: 0.0289 RE: 0.0220
Epoch 100/200 Train Loss: 0.0002 RMSE: 0.0650 RE: 0.2418
Epoch 110/200 Train Loss: 0.0002 RMSE: 0.0280 RE: 0.0110
Epoch 120/200 Train Loss: 0.0002 RMSE: 0.0465 RE: 0.0879
Epoch 130/200 Train Loss: 0.0002 RMSE: 0.0442 RE: 0.0989
Epoch 140/200 Train Loss: 0.0002 RMSE: 0.0510 RE: 0.1209
Epoch 150/200 Train Loss: 0.0002 RMSE: 0.0405 RE: 0.0769
Epoch 160/200 Train Loss: 0.0001 RMSE: 0.0270 RE: 0.0110
Epoch 170/200 Train Loss: 0.0001 RMSE: 0.0285 RE: 0.0330
Epoch 180/200 Train Loss: 0.0003 RMSE: 0.0389 RE: 0.0549
Epoch 190/200 Train Loss: 0.0001 RMSE: 0.0266 RE: 0.0110
Epoch 200/200 Train Loss: 0.0002 RMSE: 0.0320 RE: 0.0000
score_list for 4 types of batteries:
 [0.02101864 0.02660724]
```

```
rmse: for this seed: 0.0238
-----------------------------------------------------------------
Epoch 10/200 Train Loss: 0.0002 RMSE: 0.0211 RE: 1.0000
Epoch 20/200 Train Loss: 0.0002 RMSE: 0.0180 RE: 0.0526
Epoch 30/200 Train Loss: 0.0001 RMSE: 0.0295 RE: 1.0000
Epoch 40/200 Train Loss: 0.0002 RMSE: 0.0125 RE: 0.0197
Epoch 50/200 Train Loss: 0.0002 RMSE: 0.0206 RE: 0.0461
Epoch 60/200 Train Loss: 0.0001 RMSE: 0.0144 RE: 1.0000
Epoch 70/200 Train Loss: 0.0002 RMSE: 0.0140 RE: 1.0000
Epoch 80/200 Train Loss: 0.0001 RMSE: 0.0164 RE: 0.0197
Epoch 90/200 Train Loss: 0.0002 RMSE: 0.0458 RE: 1.0000
Epoch 100/200 Train Loss: 0.0002 RMSE: 0.0136 RE: 1.0000
Epoch 110/200 Train Loss: 0.0002 RMSE: 0.0203 RE: 0.0395
Epoch 120/200 Train Loss: 0.0005 RMSE: 0.0181 RE: 0.0461
Epoch 130/200 Train Loss: 0.0002 RMSE: 0.0553 RE: 0.1513
Epoch 140/200 Train Loss: 0.0002 RMSE: 0.0272 RE: 0.0329
Epoch 150/200 Train Loss: 0.0001 RMSE: 0.0360 RE: 1.0000
Epoch 160/200 Train Loss: 0.0002 RMSE: 0.0696 RE: 1.0000
Epoch 170/200 Train Loss: 0.0002 RMSE: 0.0120 RE: 1.0000
Epoch 180/200 Train Loss: 0.0001 RMSE: 0.0167 RE: 0.0395
Epoch 190/200 Train Loss: 0.0003 RMSE: 0.0195 RE: 1.0000
Epoch 200/200 Train Loss: 0.0001 RMSE: 0.0165 RE: 0.0329
score_list for 4 types of batteries:
 [0.02101864 0.02660724 0.0119506 ]
rmse: for this seed: 0.0199
-----------------------------------------------------------------
Epoch 10/200 Train Loss: 0.0001 RMSE: 0.0239 RE: 0.0127
Epoch 20/200 Train Loss: 0.0001 RMSE: 0.0238 RE: 0.0380
Epoch 30/200 Train Loss: 0.0001 RMSE: 0.0224 RE: 0.0127
Epoch 40/200 Train Loss: 0.0001 RMSE: 0.0229 RE: 0.0127
Epoch 50/200 Train Loss: 0.0001 RMSE: 0.0228 RE: 0.0127
Epoch 60/200 Train Loss: 0.0001 RMSE: 0.0224 RE: 0.0127
Epoch 70/200 Train Loss: 0.0002 RMSE: 0.0225 RE: 0.0253
Epoch 80/200 Train Loss: 0.0001 RMSE: 0.0251 RE: 0.0127
Epoch 90/200 Train Loss: 0.0002 RMSE: 0.0559 RE: 0.1139
Epoch 100/200 Train Loss: 0.0001 RMSE: 0.0278 RE: 0.0127
Epoch 110/200 Train Loss: 0.0002 RMSE: 0.0235 RE: 0.0127
Epoch 120/200 Train Loss: 0.0001 RMSE: 0.0454 RE: 0.1139
Epoch 130/200 Train Loss: 0.0001 RMSE: 0.0248 RE: 0.0127
Epoch 140/200 Train Loss: 0.0001 RMSE: 0.0227 RE: 0.0253
Epoch 150/200 Train Loss: 0.0001 RMSE: 0.0257 RE: 0.0506
Epoch 160/200 Train Loss: 0.0001 RMSE: 0.0226 RE: 0.0127
Epoch 170/200 Train Loss: 0.0001 RMSE: 0.0224 RE: 0.0127
Epoch 180/200 Train Loss: 0.0001 RMSE: 0.0249 RE: 0.0380
Epoch 190/200 Train Loss: 0.0001 RMSE: 0.0227 RE: 0.0127
Epoch 200/200 Train Loss: 0.0001 RMSE: 0.0253 RE: 0.0127
```

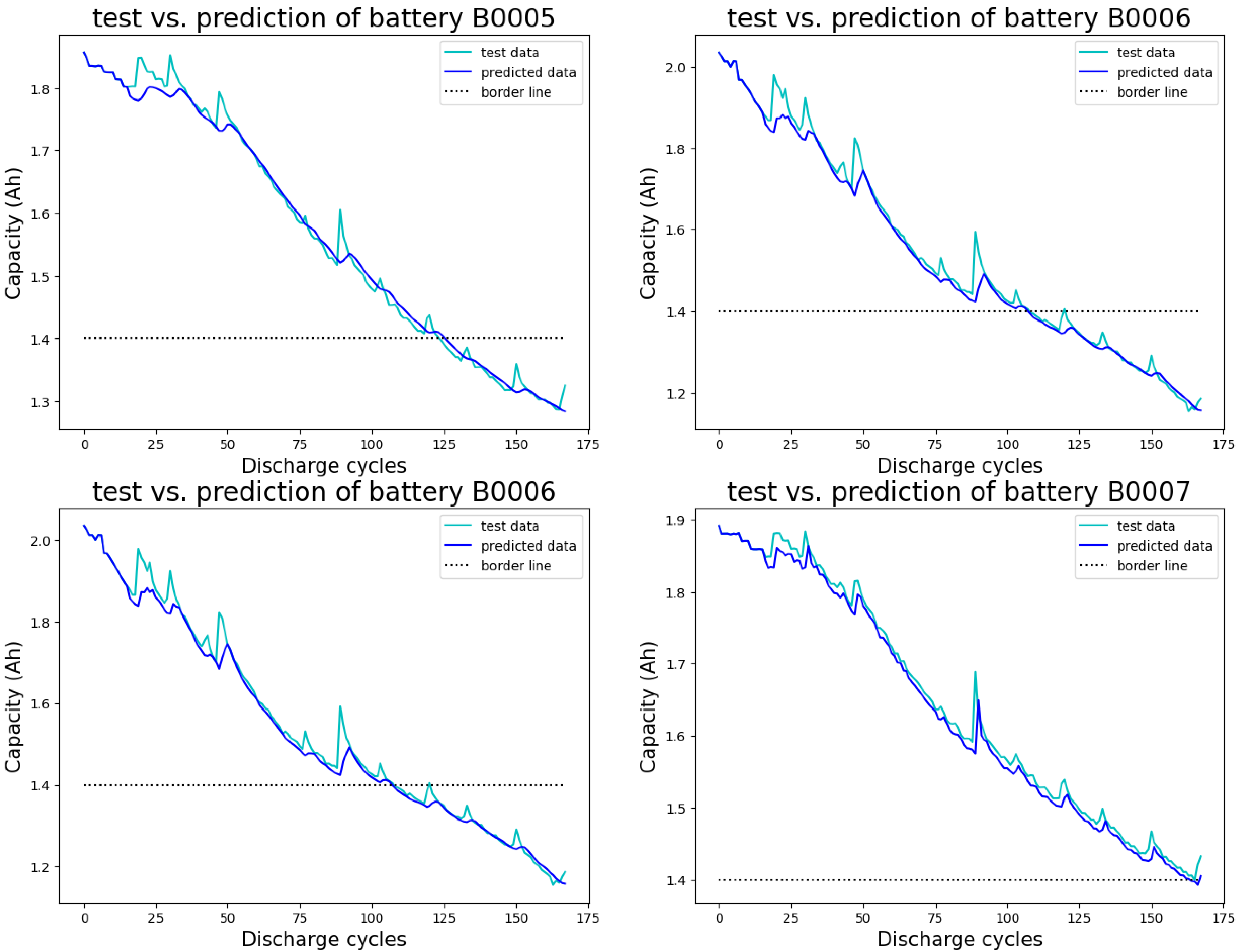
```
score_list for 4 types of batteries:
 [0.02101864 0.02660724 0.0119506  0.02236618]
rmse: for this seed: 0.0205
------------------------------------------------------------------
```

3.3 预测容量曲线

In [16]:

```python
fig,ax = plt.subplots(2, 2, figsize=(16, 12))

for i in range(2):
    for j in range(2):
        t = i + j
        battery_name = Battery_list[t]
        test_data = capacity[battery_name][1]
        predict_data = test_data[:window_size] + result_list[t]
        x = [t for t in range(len(test_data))]
        threshold = [Rated_Capacity*0.7] * len(test_data)
        ax[i][j].plot(x, test_data, 'c', label='test data')
        ax[i][j].plot(x, predict_data, 'b', label='predicted data')
        ax[i][j].plot(x, threshold, 'black', ls=':', label='border line')
        ax[i][j].legend()
        ax[i][j].set_xlabel('Discharge cycles', fontsize=15)
        ax[i][j].set_ylabel('Capacity (Ah)', fontsize=15)
        ax[i][j].set_title('test vs. prediction of battery ' + battery_name, fontsize=20)
plt.show()
```



test vs. prediction of battery B0005
test vs. prediction of battery B0006
test vs. prediction of battery B0006
test vs. prediction of battery B0007
test data
predicted data
border line
Capacity (Ah)
Discharge cycles

In [ ]:

```

```