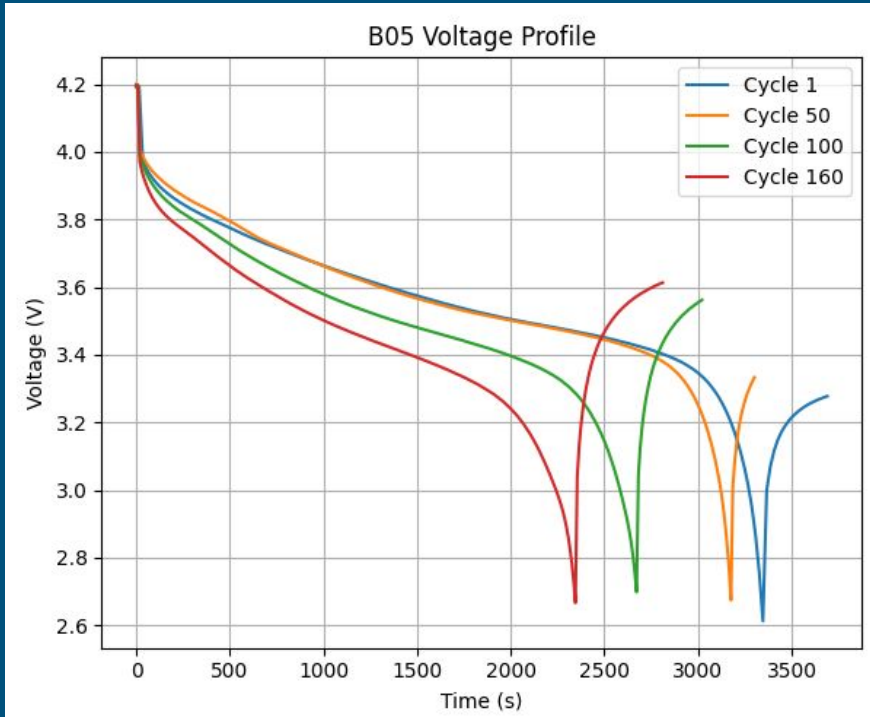
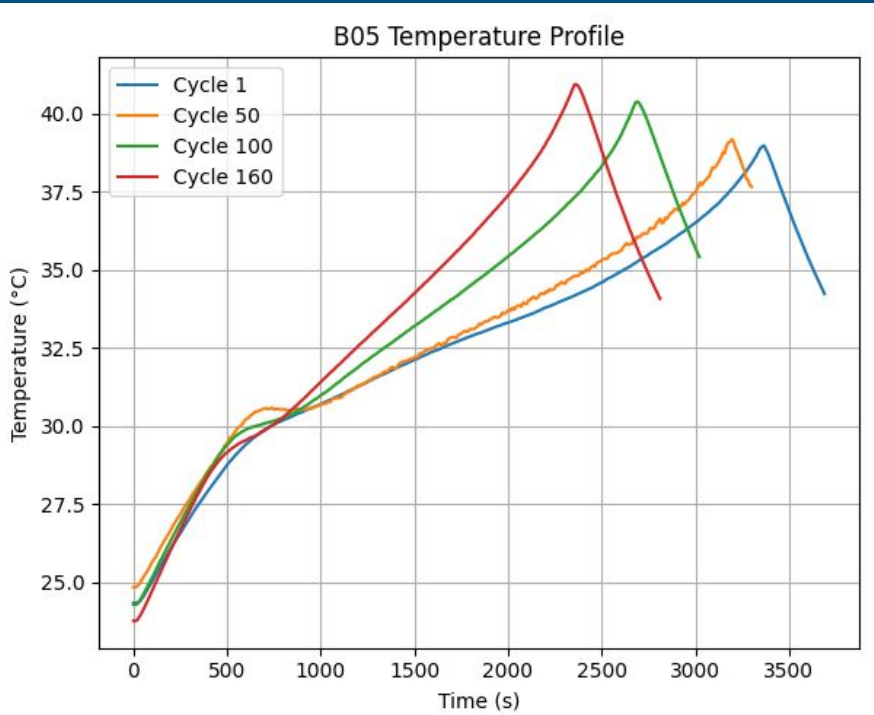
Federated Learning

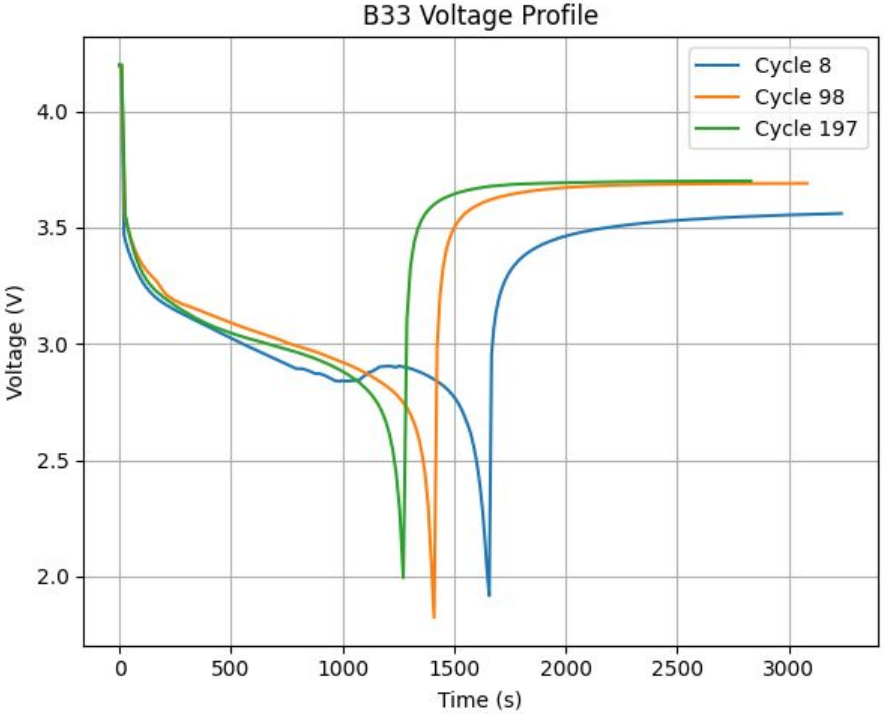
Using FL on NASA Battery Dataset 20260125-20260203

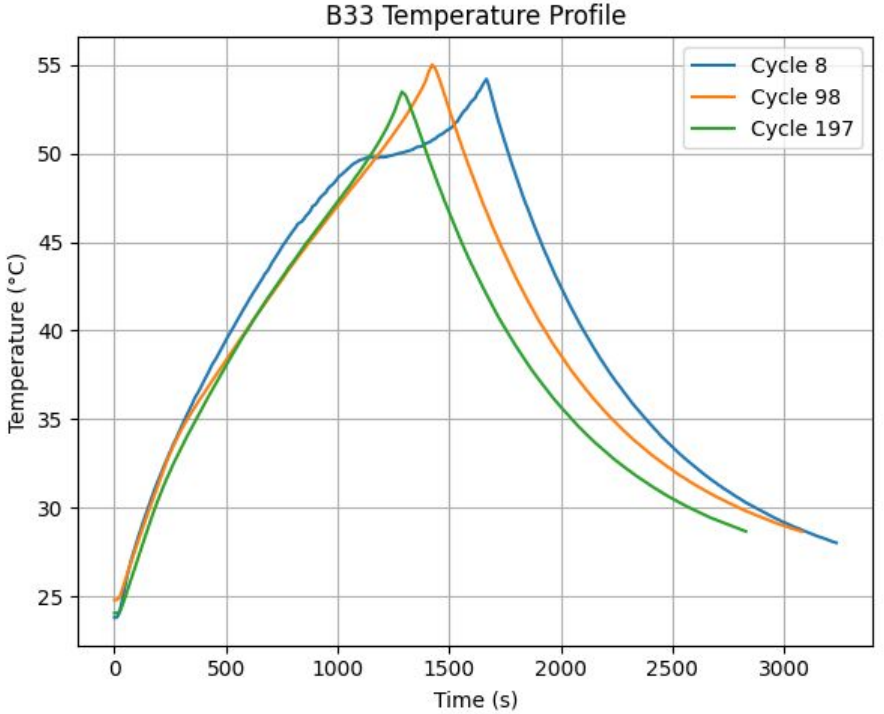
Battery State of Health (SOH) Prediction

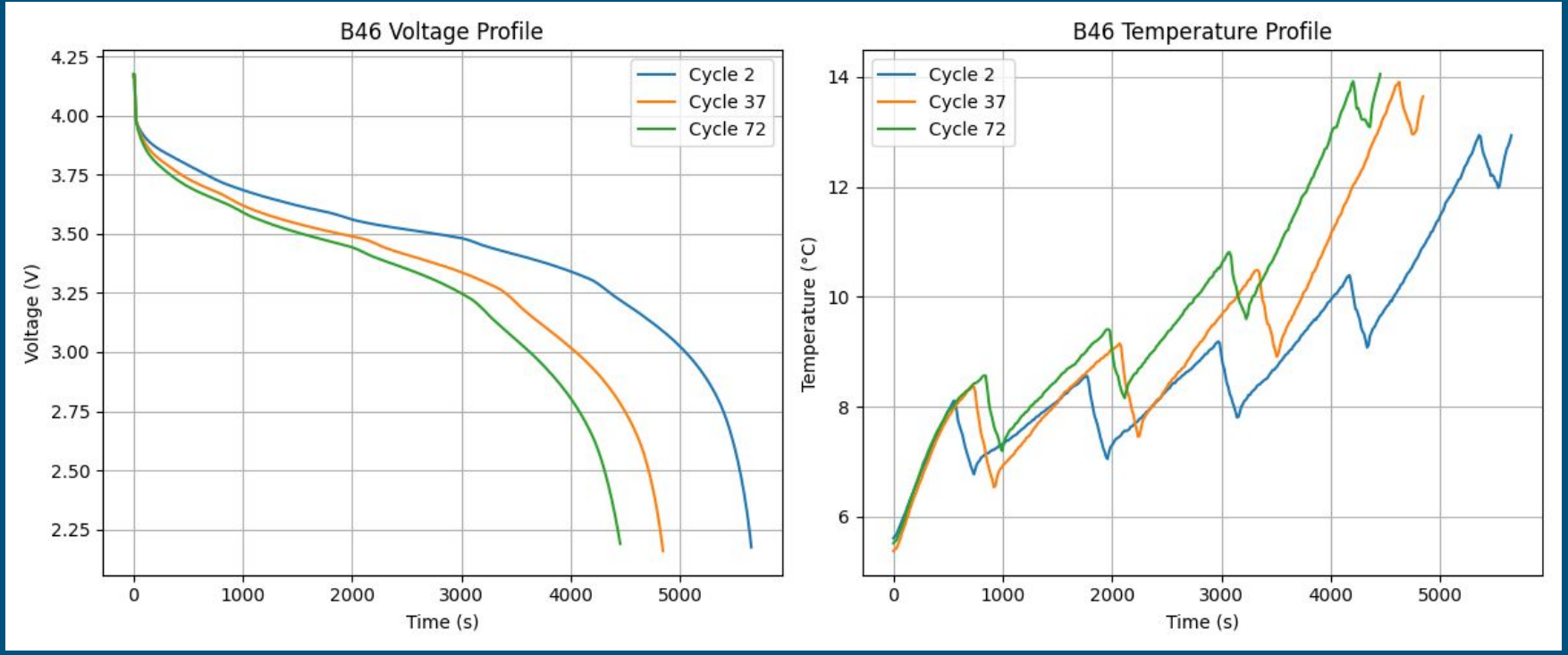
Battery ID	Temp Index	Dataset Source	processed Training Cycles	Condition Description
B48 (Client 1)	High Temp	B48_discharge_soh.csv	38	**Low Data Density**: Smaller number of recorded cycles, representing a battery with limited historical telemetry.
B33 (Client 2)	Low (4°)	B33_discharge_soh.csv	133	**High Load**: Differing discharge currents and load profiles compared to standard aging tests.
B05 (Client 3)	Room Temp (24°C)	B05_discharge_soh.csv	125	**Baseline Aging**: Standard cycle life test under controlled environmental conditions.

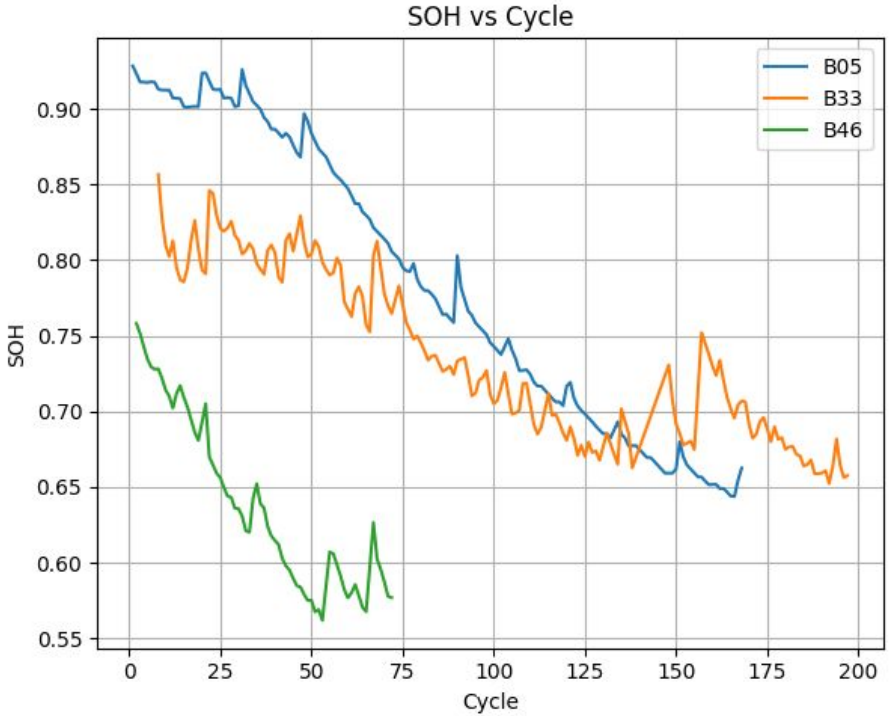

B05 Voltage Profile
Cycle 1
Cycle 50
Cycle 100
Cycle 160
Voltage (V)
Time (s)
4.2
4.0
3.8
3.6
3.4
3.2
3.0
2.8
2.6
0
500
1000
1500
2000
2500
3000
3500

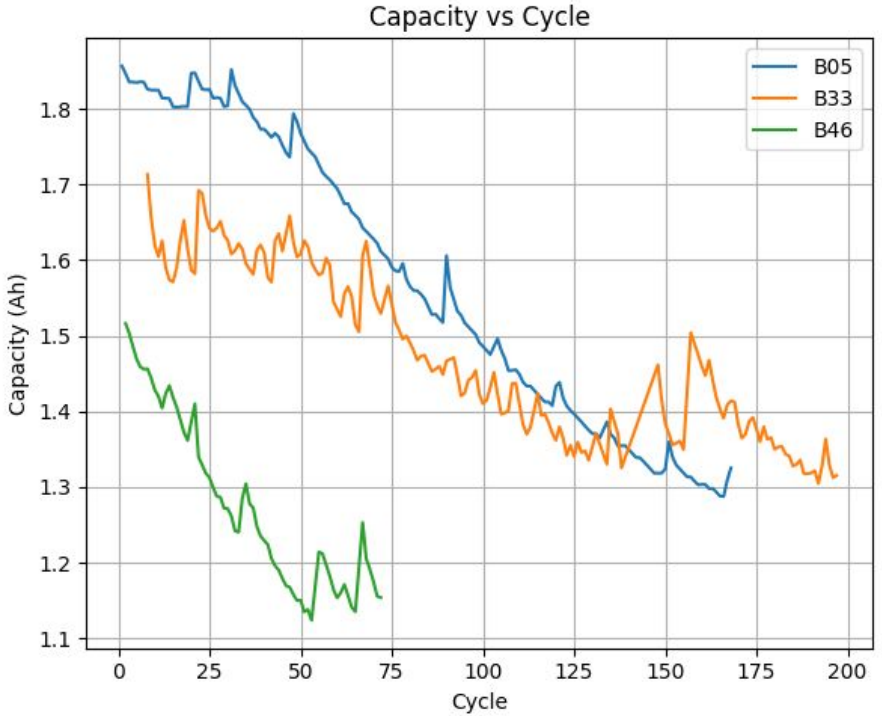

B05 Temperature Profile
Cycle 1
Cycle 50
Cycle 100
Cycle 160
Temperature (°C)
Time (s)
40.0
37.5
35.0
32.5
30.0
27.5
25.0
0
500
1000
1500
2000
2500
3000
3500


B33 Voltage Profile
Cycle 8
Cycle 98
Cycle 197
Voltage (V)
Time (s)
4.0
3.5
3.0
2.5
2.0
0
500
1000
1500
2000
2500
3000


B33 Temperature Profile
Cycle 8
Cycle 98
Cycle 197
Temperature (°C)
Time (s)
55
50
45
40
35
30
25
0
500
1000
1500
2000
2500
3000


B46 Voltage Profile
Voltage (V)
Time (s)
Cycle 2
Cycle 37
Cycle 72
4.25
4.00
3.75
3.50
3.25
3.00
2.75
2.50
2.25
0
1000
2000
3000
4000
5000
B46 Temperature Profile
Temperature (°C)
Time (s)
Cycle 2
Cycle 37
Cycle 72
14
12
10
8
6
0
1000
2000
3000
4000
5000


SOH vs Cycle
B05
B33
B46
SOH
Cycle
0.90
0.85
0.80
0.75
0.70
0.65
0.60
0.55
0
25
50
75
100
125
150
175
200


Capacity vs Cycle
B05
B33
B46
Capacity (Ah)
Cycle
1.8
1.7
1.6
1.5
1.4
1.3
1.2
1.1
0
25
50
75
100
125
150
175
200

Executive Summary

- This project aimed to transition a battery SOH prediction system from “Independent Local Learning” (isolated models) to “Federated Learning (FL)”
- The goal was to train a robust “Global Model” across multiple battery datasets (`B48`, `B33`, `B05`) without centralizing the raw data, thereby preserving privacy and efficiency.

Key achievements:

- ❏ Implemented “Federated Averaging (FedAvg)”.
- ❏ Achieved model convergence across 3 heterogeneous clients.
- ❏ Implemented “Personalization (Fine-Tuning)” to resolve performance issues for clients with smaller datasets

Methodology & Architecture

Federated Averaging (FedAvg)

Used a centralized server-client architecture:

1. Server: Maintains the Global Model.
2. Clients:
   - Download global weights.
   - Train locally on their private battery data (5 epochs).
   - Upload updated weights to the server.
3. Aggregation: Server averages client weights (weighted by dataset size) to update the Global Model.
4. **Model Architecture**: A Gated Recurrent Unit (GRU) network was used for time-series prediction, consisting of two GRU layers (60 units each) with dropout (0.2) and a final dense layer to output the SOH value.
5. **Training Parameters**: The global training consisted of 20 communication rounds.

   Each local client trained for 5 epochs per round with a learning rate of 0.001 using the Adam optimizer.

Addressing Data Imbalance (Personalization)

Identified significant data imbalance (Client 1 ~23k rows vs. others ~50k).
This biased the Global Model towards the larger clients.

Solution: Added a Personalization Step where, after global training,
Client 1 fine-tunes the global model on its local data for 10 additional epochs.

```
# Fine-tuning for Client 1 (B48)

ft_model = create_model(input_shape)

ft_model.set_weights(server.global_weights)

# Train locally for 10 additional epochs

history_ft = ft_model.fit(client1.X_train, client1.y_train, epochs=10)
```

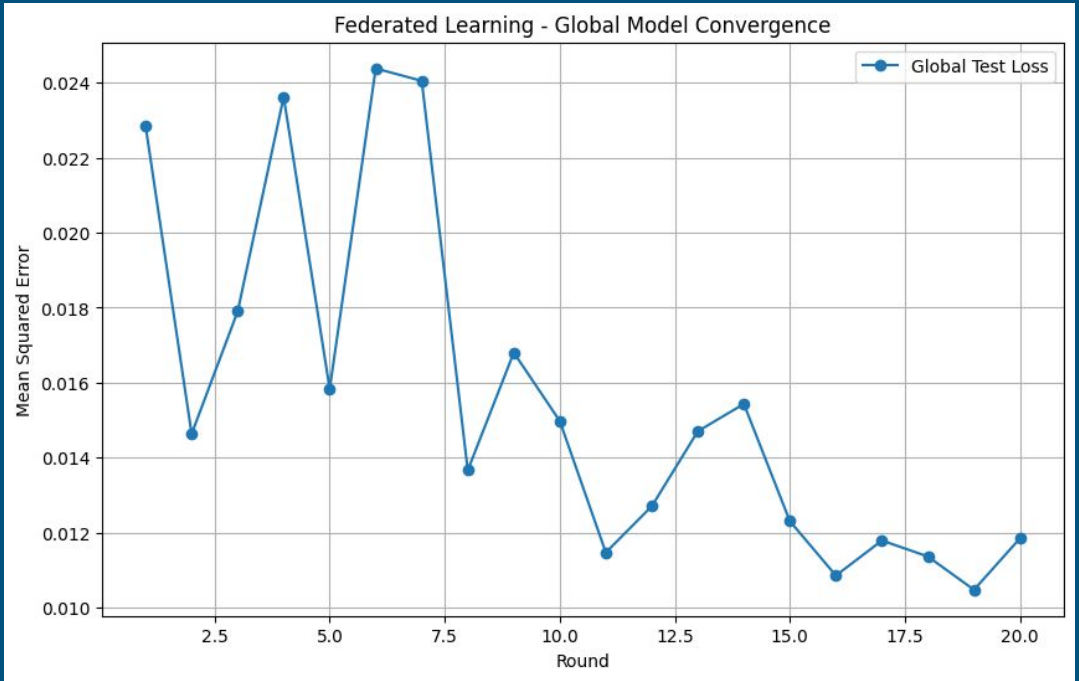
Results & Visualizations

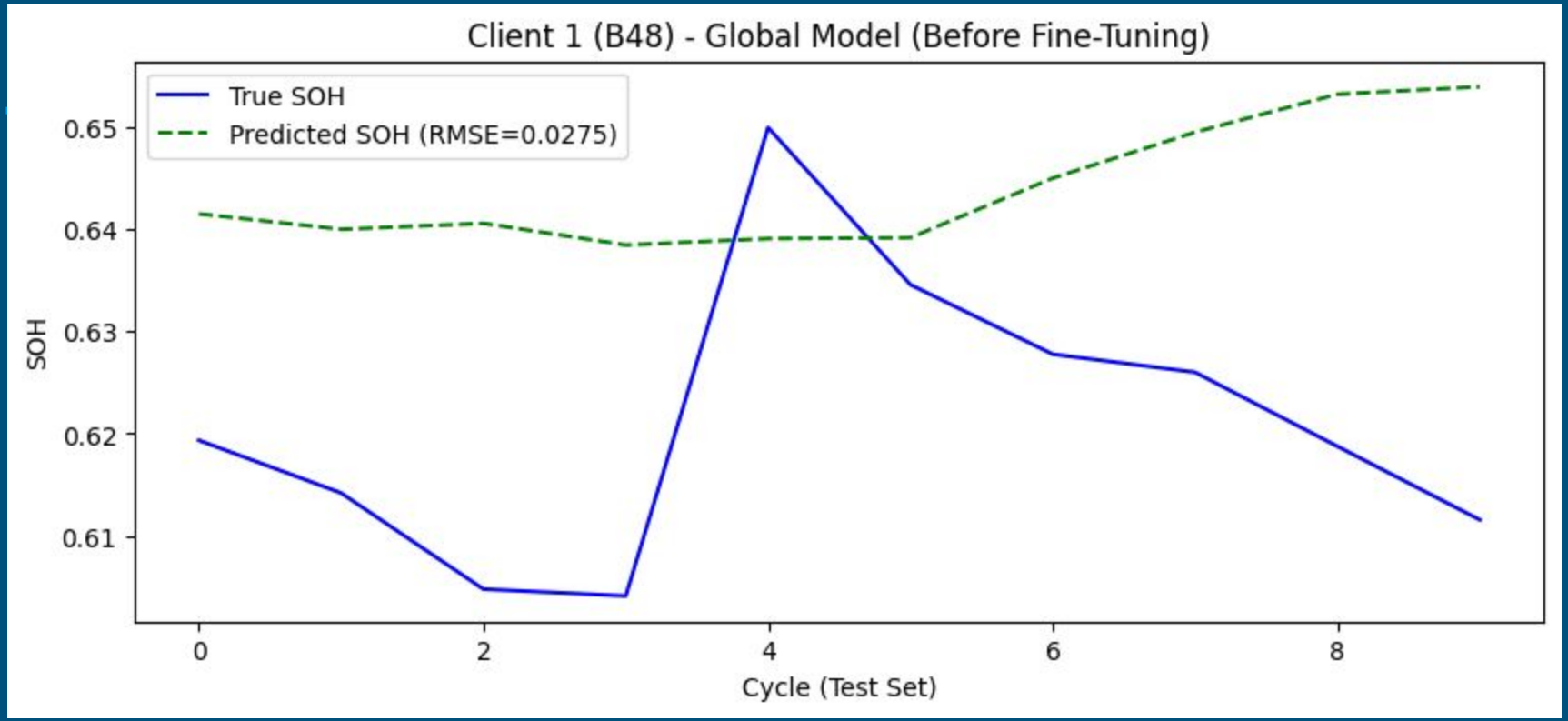
Global Model Convergence

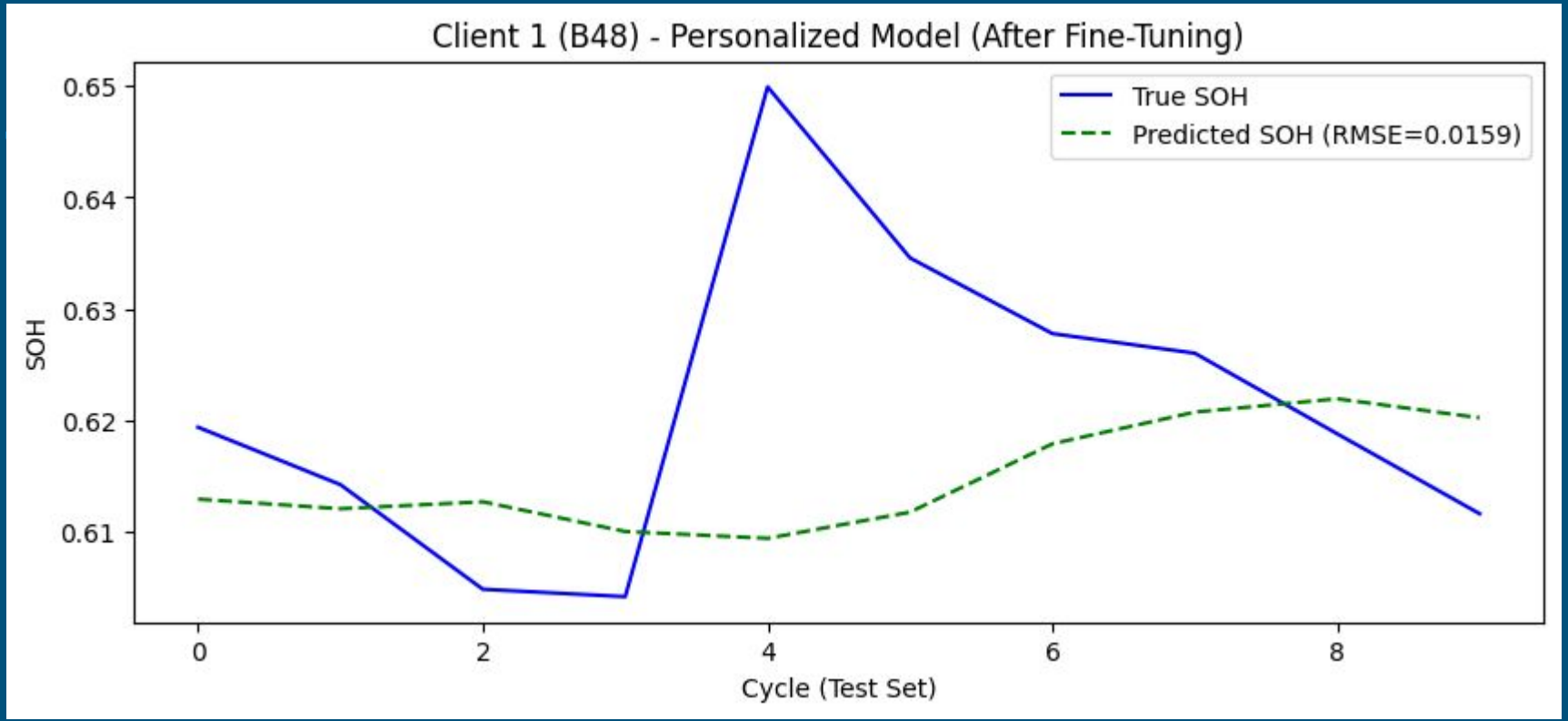
The Global Test Loss (MSE) demonstrates a clear downward trend over 20 rounds, indicating that the model successfully learned generalizable features from all batteries.

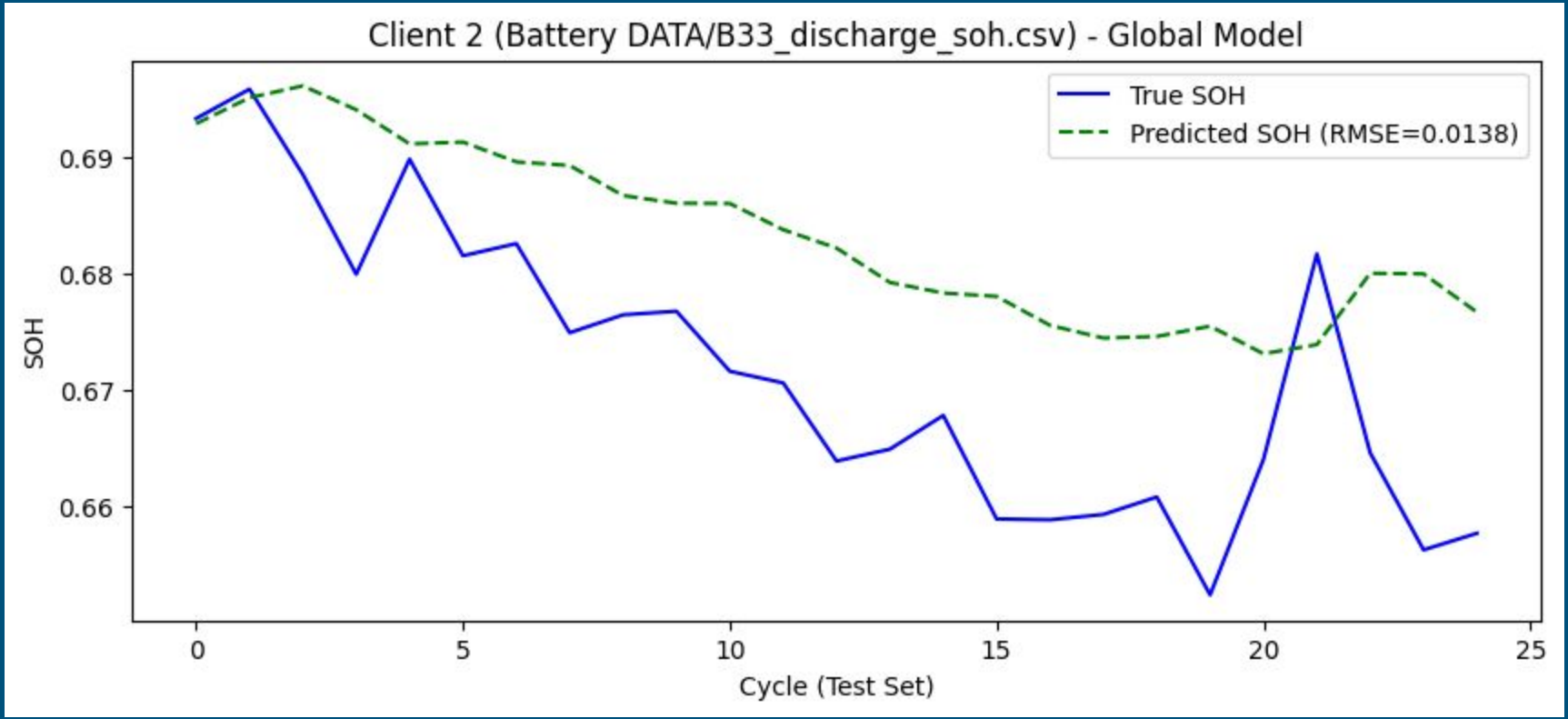
Visualization:

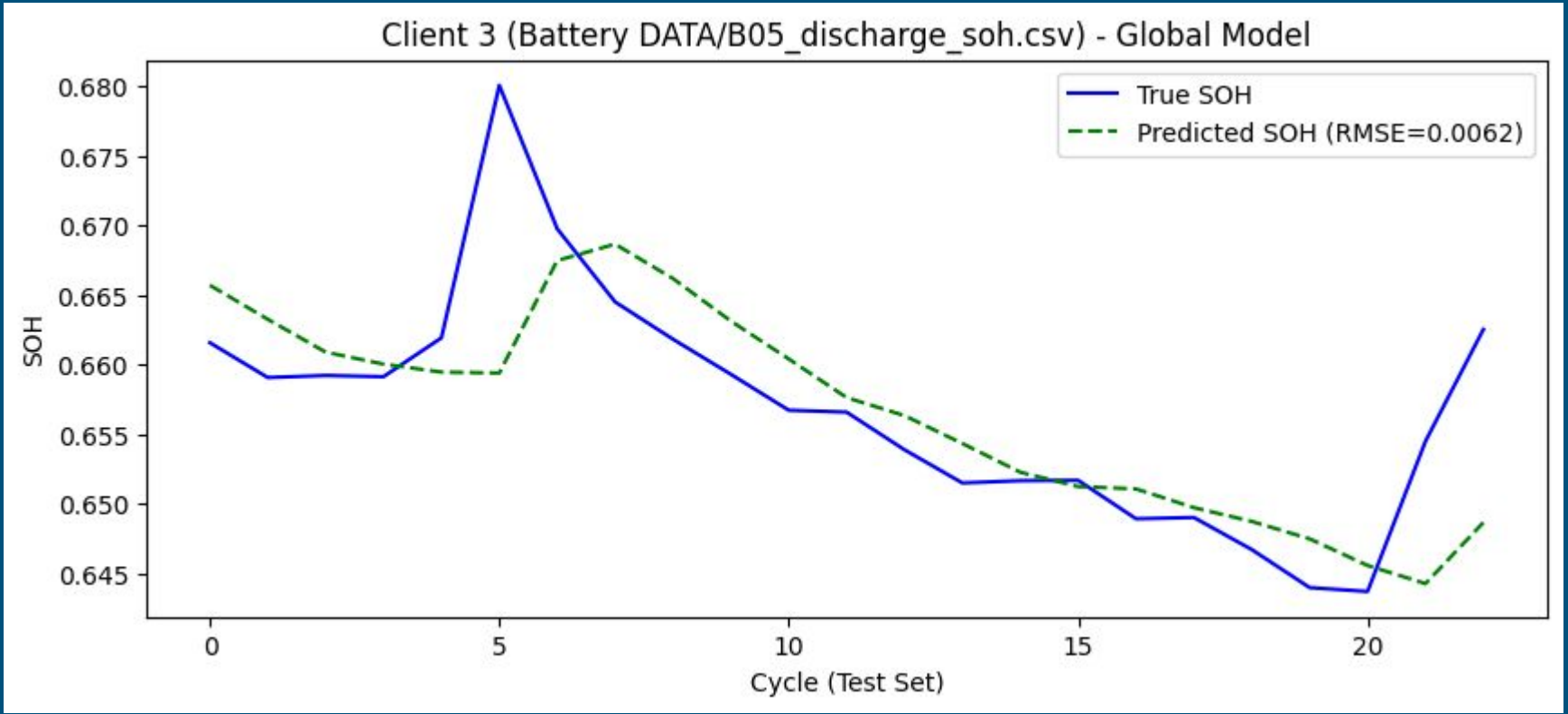
- **X-Axis**: Communication Rounds (1-20)
- **Y-Axis**: Global Test Loss (MSE)
- **Trend**: Exponential decay, stabilizing around Round 15.




Client 1 (B48) - Global Model (Before Fine-Tuning)
True SOH
Predicted SOH (RMSE=0.0275)
SOH
0.65
0.64
0.63
0.62
0.61
0
2
4
6
8
Cycle (Test Set)


Client 1 (B48) - Personalized Model (After Fine-Tuning)
True SOH
Predicted SOH (RMSE=0.0159)
SOH
0.65
0.64
0.63
0.62
0.61
0
2
4
6
8
Cycle (Test Set)


Client 2 (Battery DATA/B33_discharge_soh.csv) - Global Model
True SOH
Predicted SOH (RMSE=0.0138)
SOH
0.69
0.68
0.67
0.66
0
5
10
15
20
25
Cycle (Test Set)


Client 3 (Battery DATA/B05_discharge_soh.csv) - Global Model
True SOH
Predicted SOH (RMSE=0.0062)
SOH
0.680
0.675
0.670
0.665
0.660
0.655
0.650
0.645
0
5
10
15
20
Cycle (Test Set)

Client / Battery ID	Model Version	Mean Squared Error (MSE)	Root Mean Squared Error (RMSE)
Client 1 (B48)	Global (Before Fine-Tuning)	0.000759	0.027542
Client 1 (B48)	Personalized (After Fine-Tuning)	0.000252	0.015883
Client 2 (B33)	Global Model	0.000191	0.013811
Client 3 (B05)	Global Model	0.000038	0.006176